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The sensitivity of Fama-French factors to economic uncertainty[*]

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Preliminary version - Comments welcome

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Abstract

This paper analyzes the sensitivity of the three Fama-French factors in relation to the US economic uncertainty, by using three proxies of uncertainty measures in macroeconomics, financial markets or economic policy from January 1985 to December 2011. We examine the extent, speed and duration of response of the three (market, size and value) risk premia to movements in the US uncertainties under low and high volatility regimes through the Markov-regime switching VAR model. We find clearly two (high and low) volatility regimes, where each regime is highly persistent. The high volatility regime is the prevailing regime between periods of 2000 to 2003, and 2008 to the end of 2012. We show a negative effect of changes in financial and economic policy uncertainties on value risk premia during the high volatility regime. This finding imply that investors move to growth stocks from value stocks in high volatility regime when volatility is expected to increase. The latter suggests that value firms can be more risky than growth firms during high volatility periods. We also propose an aggregate measure of economic uncertainty by using Principal Component Analysis based on the three uncertainty proxies. The results on value risk premia are confirmed. We find a negative relationship between the market risk premium and the change in the economic uncertainty index in high volatility regime. Finally, by adding a liquidity risk factor we find a positive effect of financial uncertainty on liquidity factor during the high volatility regime, suggesting that investors preferring liquidity stocks when market uncertainty increases.

Keywords: Fama-French factors; Economic uncertainty; Markov-switching model.

JEL Classification: G10; G11; C32.

1 Introduction

The Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) remains a benchmark asset pricing model for both financial economists and investment practitioners, which relates required or expected returns to systematic risk (or market beta) and not related to other variables.[1] However, some firm-specific characteristics besides the market beta have been documented to have significant explanatory power for average returns, for example, firm size (e.g., Banz, 1981; Reinganum, 1981, 1982), and book-to-market equity ratio (B/M) (e.g., De Bondt and Thaler, 1985; Fama and French, 1992). Motivated by the growing empirical evidence on these CAPM anomalies, Fama and French (1993) propose a three-factor model (FF) that adds two factors to the market risk premium, size and value (premia) factors.

It is considered that value (growth) stocks are riskier than growth (value) stocks in bad (good) times (e.g., Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001b; Petkova and Zhang, 2005; Zhang, 2005; Chen et al., 2008), suggesting that investors tend to switch from riskier assets to safer ones in bad times. Further, since small firms are relatively more sensitive to economic downturns than large firms (e.g., Gertler and Gilchrist, 1994; Fort et al., 2013), investors tend to move out of small stocks in bad times.

It is also well-known that uncertainty about the future has real implications on economic agents' behavior (e.g., Dixit, 1989; Bernanke, 1983; Bloom et al., 2007; Bloom, 2009). Growing literature provide evidence that economic uncertainty affect financial markets, especially firm fundamentals, such as cash flows, risk-adjusted discount factors, and investment opportunities (e.g., Bloom, 2009; Bloom, Bond, and Van Reenen, 2007), equity portfolios and individual stocks (e.g., Anderson et al., 2009; Bekaert et al., 2009; Bali and Zhou, 2013), and volatility (e.g., Veronesi, 1999; Bansal and Yaron, 2004; Bloom, 2009). Recently, Brogaard and Detzel (2013) show that uncertainty related specifically to the economic policy of governments may impact financial markets. Economic uncertainty is difficult to quantify since it is intrinsically unobservable concept, and there are different sources of uncertainty, but it is possible to observe uncertainty indirectly using a number of proxy indicators (Bloom, 2013; Bloom et al., 2013).

This paper analyzes the sensitivity of three Fama-French factors (1993) in relation to the US economic uncertainty, by using three proxies of uncertainty measures in macroeconomics, financial markets or economic policy.[2] We use the index of economic policy uncertainty proposed by Baker,

[1] See Shih et al. (2014) for a survey on the evolution of CAPM during the last four decades.

[2] Knight (1921) established a distinction between risk and true uncertainty. Risk refers to the possibility of a future outcome

Bloom and Davis (2013), the CBOE volatility index as proxy of financial market uncertainty, and the macro uncertainty factor developed by Jurado et al. (2013). Specifically, we investigate whether the uncertainty measures have a direct and systematic effect on equity returns by increasing or decreasing the returns of the systematically priced factors included in the Fama and French (1993) model. In addition to specific measures of uncertainty, we use a statistical approach to develop an aggregate measure of economic uncertainty. To sufficiently capture the common variation among the correlated factors of economic policy, financial and macroeconomic uncertainty, we apply the principal component analysis that uses orthogonal transformation to convert a set of highly correlated indicators into a set of linearly uncorrelated variables called principal components. We then examine the sensitivity of three Fama-French factors to this economic uncertainty index.

In particular, we examine the extent, speed and duration of response of the three (market, size and value) risk premia to movements in the US uncertainties under low and high volatility regimes through the application of Markov regime switching (MS) analysis (Hamilton, 1989). The MS models have become popular in the financial literature because they can capture the instability of financial time series, such as sudden (transitory or short-lived) or persistent changes of behavior (Ang and Timmermann, 2011).[3] One of the major advantages of this approach is that it does not require prior specifications or dating of volatility regimes. Thus, the use of the MS model allows a more robust and informative analysis on the sensitivity of three Fama-French factors. To the knowledge of the authors, no study on the three Fama-French factors has yet utilized the MS approach.[4] In order to measure the extent of the response of three Fama-French factors to movements in the uncertainty in economic policy, financial markets and macroeconomics, a Markov Switching Vector Autoregressive Model (MS-VAR) is estimated. With this model, an impulse response analysis is then conducted afterwards to determine the speed and duration of the response. This approach allows us to analyze the effects of uncertainty in high and low volatility periods.

The remainder of this paper is organized as follows: Section 2 briefly describes the methodology of MS-VAR. The data are presented in Section 3. Section 4 discussed the empirical results. Finally, Section 5 concludes.

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for which the probabilities of the different possible states of the world are known. Uncertainty refers to a future outcome that has unknown probabilities associated with the different possible states of the world. Note that some of what we call uncertainty may indeed be risk as defined by Knight (1921). Thus, we use different proxies for economic uncertainty, which can be different from Knightian uncertainty.

[3]See Guidolin (2012) for a survey on applications of Markov regime switching models in empirical finance.

[4]Durand et al. (2011) and Shamsuddin and Kim (2014) analyze the effect of the market uncertainty (using the VIX index) on the three Fama-French factors but using a standard VAR model without regime switching.

2 Data

We consider monthly data for three Fama-French factors from January 1985 to December 2011: market (MKT= $Rm - Rf$)), size (Small Minus Big, SMB) and value (High Minus Low, HML) factors. The market return (Rm) is the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ, and the risk-free rate (Rf) is the one-month Treasury bill rate. The SMB factor is the difference between the returns on the portfolio of small size stocks and the returns on the portfolio of big size stocks. The HML factor is the difference between the returns on the portfolio of high book-to-market stocks and the returns on the portfolio of low book-to-market stocks. The data for Rm, Rf, SMB and HLM come from Kenneth French's website (see Figure 11).[5] We use three proxies of US uncertainty measures in macroeconomics, financial markets or economic policy. The US macroeconomic uncertainty variable (UMACRO) is the macro uncertainty factor developed by Jurado et al. (2013), based on a large number of economic time series. For the uncertainty measure in US financial markets we employ the CBOE volatility index (VXO), also known as the "fear index" or the "fear gauge", based on trading of S&P 100 (OEX) options.[6] The VXO reflects market uncertainty associated with future stock price movements and might proxy risk aversion. The US economic policy uncertainty variable that we use is the index of economic policy uncertainty (EPU) proposed by Baker, Bloom and Davis (2013), built on three components: (i) the frequency of newspaper references to economic policy uncertainty, (ii) the number of federal tax code provisions set to expire, and (iii) the extent of forecaster disagreement over future inflation and government purchases.[7] The span of the data is 1985:1 to 2011:12 which enables us to look at the pre- and post-crisis periods to discover the impact volatility in different economic environments.

Figure 1 displays the three proxies of uncertainty. All uncertainty measures are higher during the 2001 economic recession and much higher during the 2008 global financial crisis. During the 1990 economic recession the economic policy uncertainty is higher, and the financial uncertainty is moderately high. The economic policy and financial uncertainties also present a spike around the LTCM and Russian

[5] The data are available on mba.tuck.dartmouth.edu/pages/faculty/ken.french/DataLibrary/.

[6] As an alternative to the VXO index, we could have used the newer VIX index, which was introduced by the CBOE on September 22,2003. The VIX is obtained from the European style S&P500 index option prices and incorporates information from the volatility skew by using a broader range of strike prices than just at-the-money strike series as in the VXO. However, the daily data on VIX starts from January 2, 1990, which does not cover our full sample period, beginning in January 1986. The pre-1986 VXO data are calculated by Bloom (2009). See Whaley (2009) for a history of the VIX and a summary on its calculation.

[7] See Baker et al. (2013) for a detailed description of the EPU indexes. The data are available on www.policyuncertainty.com/index.html.

Debt crisis of 1998. Higher uncertainty is also displayed during the October 1987 financial crisis for the VXO, and the July 2011 debt ceiling dispute.

Table 1 provides summary statistics for the variables used in this study. The mean of the three factors is positive, except for SMB. The risk premium factor displays the higher mean and volatility, in terms of standard deviation. ΔVXO is the most volatile among the uncertainty measures. The three factors exhibit negative skewness, except HML, while the three uncertainty measures display positive skewness. Excess kurtosis is observed for all variables, showing that their empirical distributions are leptokurtic, i.e. with substantially fatter tails (than the normal distribution). The Jarque-Bera test statistic is significant at the 1% level of significance for all series, indicating that the variables are highly non-normal. We also conduct the LM test of Engle (1982) for ARCH conditional heteroscedasticity.[8] This test statistic is significant for all uncertainty measures, indicating that they show strong conditional heteroscedasticity, whereas it is non significant for the risk premium and size factors.

Table 1. Descriptive statistics

	Min	Max	Mean	S. dev.	Med.	Kurtosis	Skewness	JB test *	Engle LM test**
MKT	-23.2400	12.4600	5.7019e-01	4.6160	1.1500	5.5445	-0.8832	129.1273 (1.0000e−03)	4.1559 (5.2720e−01)
SMB	-22.0200	8.4600	-1.3344e-01	3.2564	-0.1600	11.0036	-1.3584	961.4616 (1.0000e−03)	5.5645 (3.5092e−01)
HML	-9.8600	13.8700	3.9133e-01	3.0884	0.2500	5.6469	0.5737	112.0088 (1.0000e−03)	13.8498 (1.6592e−02)
ΔVXO	-12.4161	32.2351	1.7851e-02	4.0333	-0.1995	18.4620	2.3841	3523.4894 (1.0000e−03)	12.2971 (3.0936e−02)
ΔEPU/100	-0.6045	1.0377	2.3627e-03	0.1760	-0.0106	9.0484	1.1105	558.7414 (1.0000e−03)	22.9068 (3.5170e−04)
ΔUMACRO/100	-0.4527	0.5992	1.1506e-03	0.1392	-0.0040	4.6183	0.1877	37.1408 (1.0000e−03)	77.5073 (2.7756e−15)

* In brackets, critical values for the tests. ** With 5 lags.

Table 2 displays the correlations for the whole sample. The results show a negative correlation between uncertainty measures and risk premium factors, suggesting that an increasing in economic uncertainty is associated with a falling market, especially from financial uncertainty (-0.56). This result is consistent with the findings of Merton (1980), Fleming et al. (1995), Ang et al. (2006), and Durand et al. (2011). Merton (1980) point out that the market risk premium should be positively related to the variance of the market portfolio and that greater levels of risk should induce a larger market risk premium. French et al. (1987) show that the expected market risk premium is positively related to expected volatility and negatively related to unexpected changes in volatility. Ang et al. (2006) report a negative relationship between returns and changes in expected volatility, using changes in the VXO.

[8]The LM test is applied on the residuals of the ARMA model, where the lag length is selected based on the Akaike information criterion.

Figure 1. Economic policy, Financial and Macroeconomic Uncertainties.

Notes: Shaded regions are NBER recession dates. The data are monthly and span the period 1985:01-2011:12.

Durand et al. (2011) show that changes in the VIX drive variations in the expected returns of the factors included in the Fama-French three-factor model. We also find that uncertainty measures are negatively correlated with SMB, that might also be consistent with a flight-to-quality interpretation as increasing uncertainty may lead to investors being less willing to hold small stocks. Campbell (1993, 1996) assume that investors want to hedge against the changes in the forecasts of future market volatilities.[9] The correlations between HML and uncertainty measures are positive and very low, as found in Durand et al.

[9]Bali and Engle (2010) use implied volatility from the S&P100 index options (VXO) to test whether stocks that have higher correlation with the changes in future market volatility yield lower expected return in an ICAPM.

(2011). The results show that HML is negatively correlated to MKT (-0.27) and SMB (-0.33). Finally, the three measures of uncertainty are positively correlated, with the highest correlation between financial and economic policy uncertainties (0.39).

Table 2. Correlations.

	MKT	SMB	HML	ΔVXO	ΔEPU/100	ΔUMACRO/100
MKT	1.00	0.19	-0.27	-0.56	-0.27	-0.18
SMB		1.00	-0.33	-0.23	-0.14	-0.10
HML			1.00	0.08	0.05	0.02
ΔVXO				1.00	0.39	0.25
ΔEPU/100					1.00	0.15
ΔUMACRO/100						1.00

3 MS-VAR model

Markov-Switching vector autogressive (MS-VAR) model developed by Krolzig (1997) provides a convenient framework to analysis multivariate changes in regimes. Applied to the Fama-French factors, the Markov-switching framework offers the possibility to model high and low volatility periods as switching regimes of the stochastic process that generates changes in the expectation of market volatility.

The model is described by equation 1. In this general specification all parameters (mean, variance and autoregressive parameters) are allowed to switch between regimes according to hidden Markov chain. In the terminology of Krolzig (1997) this specification is a Markov switching intercept autoregressive heteroskedastic VAR model, MSIAH(m)-VAR(p) model, with m the number of variables and p the lag order.

$$Y_t = \begin{cases} a_1 + B_{11}Y_{t-1} + \ \dots \ + B_{p1}Y_{t-p} + A_1 u_t & if \quad s_t = 1 \\ \vdots & \\ a_m + B_{1m}Y_{t-1} + \dots + B_{pm}Y_{t-p} + A_m u_t & if \quad s_t = m \end{cases} \tag{1}$$

The Y_t is a vector of endogenous variables which depends upon an unobserved regime variable s_t that controls the state of the economy. Each regime is characterized by an intercept a_i, a K dimensional vectors of auto-regressive terms $B_{1i}, \dots, B_{pi}$, a matrix A_i, and fundamental disturbance u_t, with $u_t \sim N(0, I_K)$. Matrix A_i is computed from the regime-dependent variance covariance matrix from the reduced form VAR, Σ^i:

$$\Sigma^i = E\left(A^i U_t U_t' A^{i'}\right) = A^i I A^{i'}$$

In order to compute A^i, which has K^2 elements and K being the number of variables, from Σ^i having only $\frac{K(K+1)}{2}$ elements, sufficient restrictions are imposed, to reach a complete identification, based on the recursive structure using Choleski identification scheme. In this specification, the order of variables matters. Following Durand et al. (2011), identification is achieved by assuming that Fama-French factors (MKT, SMB and HML) do not respond contemporaneously neither to the change in the implied volatility index (ΔVIX), nor to the two measures of uncertainty (EPU and UMACRO). In other words, the ordering of the variables in the MSIAH(4)-VAR(p) is MKT, SMB, HML and either ΔVIX, or one of the measure of uncertainty (ΔEPU or ΔUMACRO).[10]

According to Turner et al. (1989), Kim et al. (2004), and Abdymomunov and Morley (2011) who found that stock market volatility follows a two-state Markov-switching process, with the market risk premium varying across the "low" and "high" volatility regimes, [11] we assume that the number of regimes $m = 2$, s_t.[12] These two regimes conventionally corresponds to the low mean change in volatility or stable state and the high mean change in volatility or volatile state, respectively. $s_t = \{1,2\}$ is assumed to follow the discrete time and discrete state stochastic process of a hidden Markov chain and controlled by transition probabilities $p_{i,j} = Pr(s_{t+1} = j | s_t = i)$, and $\sum_{j=1}^{2} p_{ij} = 1 \forall i, j \in (1,2)$. The stochastic process is defined by the transition matrix P as follows:

$$p = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$$

The model is estimated using the Expectation-Maximization (EM) algorithm as suggested by Krolzig (1997) (and in Hamilton (1994) for the univariate case), which consists of two steps whereby

[10]In this paper, we estimate three MSIAH(4)-VAR(p) models. In each model we include Fama-French factors and either ΔVIX or one of uncertainty measures, ΔEPU or ΔUMACRO. Of course it would be better to estimate only one model including all our variables, but we retain this solution in order to estimate a more parsimonious models as possible. Indeed, within VAR models, the number of variables cannot be enlarged very much, because of both estimation and identification problems. This problem is even more present within MS-VAR models as the number of parameters to estimate grows not only with the number of variables included in the model but also with regimes.

[11]Schwert (1989), Schaller and van Norden (1997), Kim et al. (1998, 2001, 2004), Hess (2003) and Mayfield (2004), among many others, have modeled monthly stock return volatility using a Markov-switching specification, with high volatility regimes typically corresponding to periods of recession and low volatility regimes typically corresponding to periods of expansion.

[12]We have also estimated a three-state regime models but the third regime is merely capturing a few extreme outliers in the data, rather than persistent changes in volatility. This result is consistent with the finding of Hamilton and Susmel (1994) and Abdymomunov and Morley (2011).

the expectation step infers the hidden Markov chain conditioned on a given set of parameters, and the maximization step re-estimates the parameters based on the inferred unobserved Markov process. These steps are repeated until convergence.

Our decision to use MS-VAR framework is also motivated by the possibility to derive regime-dependent Impulse Response Functions (IRFs), which helps to determine the cyclical variation in the responses of factors to a particular shock. For the MS-VAR models, Ehrmann et al. (2003) have developed the regime-dependent IRFs which permit to simulate the responses of endogenous variables to exogenous shocks. Such response functions are conditional on the prevailing regime at the time of the shock and on the entire horizon of the response. The regime-dependent IRF[13] is described by equation 2, which traces the expected path of the endogenous variables at time $t+h$ following a one standard deviation shock to the kth initial disturbance at time t, conditional on regime i.

$$\theta^i_{k,h} = \frac{\partial E_t Y_{t+h}}{\partial U_{k,t}} | s_t = ... = s_{t+h} = i, \quad for\ h \geq 0 \tag{2}$$

where $\theta^i_{k,1} \cdots \theta^i_{k,h}$ are K dimensional response vectors of the responses of the endogenous variables to a shock to the k^{th} fundamental disturbance. To account for estimation uncertainty, we adopt the standard bootstrapping method to get the related confidence bands by retaining the mean along with the relevant percentiles of the numerical approximation of the distribution of the original estimates of the regime vectors.[14]

4 Empirical results

4.1 Specific uncertainty measures

In this section, we examine the three MSIAH(4)-VARs, using one of the three proxies of US uncertainty in financial markets, macroeconomics or economic policy, respectively. The MSIAH(4)-VAR(1) model[15] is considered according to the specification tests (see Technical Appendix). In all MSIAH(4)-VAR(1) models, the linearity test suggests that the model is significantly non-linear and parameters switch substantially between regimes. Moreover, for the three MSIAH(4)-VAR(1) models, each regime is highly persistent according to the transition matrix (Table 6, Appendix A), with transition probabilities lying between 87% and 96% month-to-month probabilities of remaining in the low and high volatility regimes, respectively. Inferences regarding the turning points can be obtained from the smoothed

[13]The estimation method, identification and impulse response are detailed in Ehrmann et al. (2003).

[14]In this analysis, we use 1000 bootstrap replicates.

[15]The number of lags is set equal to one according to all information criteria displayed in the Technical Appendix.

probabilities of regimes (Figure 2). The timing of the change across regimes and the number of months for which factors were under the two regimes are very similar. These results suggest that there are clearly two different volatility regimes. Note that the first regime, corresponding to the high volatility regime, is the prevailing regime between periods of 2000 to 2003, and 2008 to the end of 2012. These periods correspond the bear market following the burst of the dot-com bubble and Fed's interventions, and the 2007-2008 financial crisis and the related recession[16], respectively. The second regime, corresponding to the low volatility regime, coincides with the two bull market periods; the first was part of the dot-com bubble and the second corresponds to the mortgage market bubble.

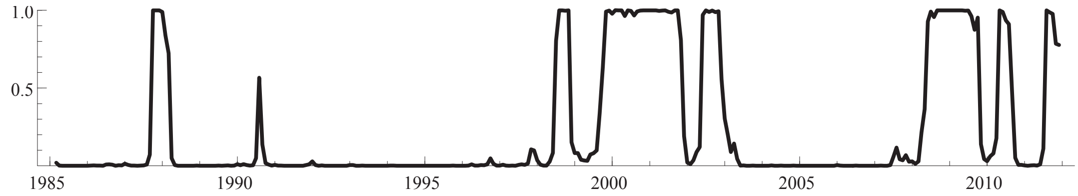
We also find clear spikes, commune to the three MSIAH(4)-VAR(1) models, corresponding to stock market crash in October 1987 and the LTCM and Russian Debt crisis of 1998. A specific spike is found from MSIAH(4)-VAR(1) using EPU in 1992 associated with the presidential election (Figure 17b). These changes can be considered as extreme outliers, as suggested by Hamilton and Susmel (1994) who find that "*extremely large shocks, such as the October 1987 crash, arise from quite different causes and have different consequences for subsequent volatility than do small shocks.*"

We use MSIAH(4)-VAR(1) to examine the sensitivity of three risk premia (MKT, SMB and HML) to changes in macroeconomics (ΔUMACRO), financial markets (ΔVXO) or economic policy (ΔEPU) uncertainties, under low and high volatility regimes. To analyze how changes in uncertainty impact the risk premia we examine the impulse response functions (IRFs) derived from the MS-VAR, according to the two volatility regimes. The IRFs are reported in Figure 3 along with 90% confidence band computed with standard bootstrap. Figures 3 to 5 display how the three risk premia respond to a one standard deviation innovation in ΔVXO, ΔEPU and ΔUMACRO, respectively. The impulse reaction period is chosen to be 6 months. Table 3 reports the effect size estimates from the impulse response functions with the cumulative responses. This indicates the response values of a (risk premia) variable to a standard deviation innovation (uncertainty) shock to other over the time horizon from 0 to 6 months.

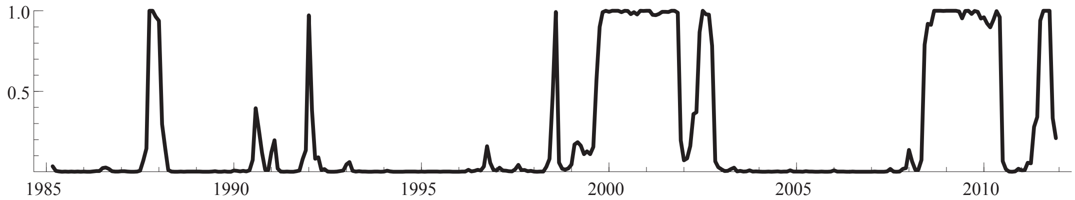
The IRFs show a positive effect of a shock to ΔVXO on SMB only during the low volatility regime (3), implying that investors prefer larger stocks over smaller stocks in low volatility regime whereas they move to growth stocks from value stocks in high volatility regime when volatility is expected to increase. We also find that a negative effect of ΔVXO on HML during the high volatility regime, suggesting that value firms can be more risky than growth firms during high volatility periods. This is consistent with the view that value is riskier than growth in bad times when the price of risk is high (e.g., Jagannathan

[16]This result confirms the findings of Schwert (1989), Hamilton and Lin (1996) and Charles and Darné (2014) that volatility of stock returns increases during (severe) recessions.

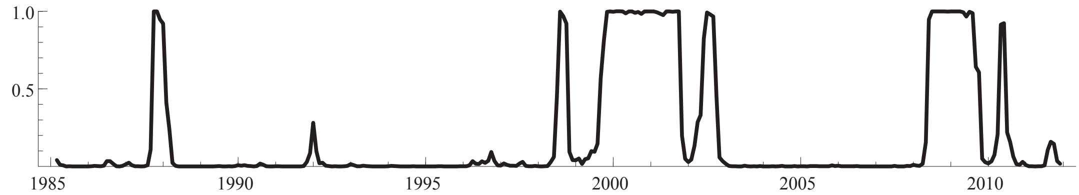
Figure 2. Estimated smoothed probabilities for MSIAH(4)-VAR(1) models



(a) MSIAH(4)-VAR(1) with VXO



(b) MSIAH(4)-VAR(1) with EPU



(c) MSIAH(4)-VAR(1) with UMACRO

Note: the timeline of the figure indicates two regimes describing the sample period for different models. Regime 1, corresponding to the high volatility regime, is represented over periods of 2000 to 2003, and 2008 to the end of 2012.

and Wang, 1996; Lettau and Ludvigson, 2001b; Petkova and Zhang, 2005; Zhang, 2005; Chen et al., 2008). We do not find evidence of the effect of ΔVXO on MKT, whatever the volatility regime. This result is in contrast with Durand et al. (2011) and Shamsuddin and Kim (2014) who found a negative relationship between the market risk premium and unexpected changes in expected volatility.[17]

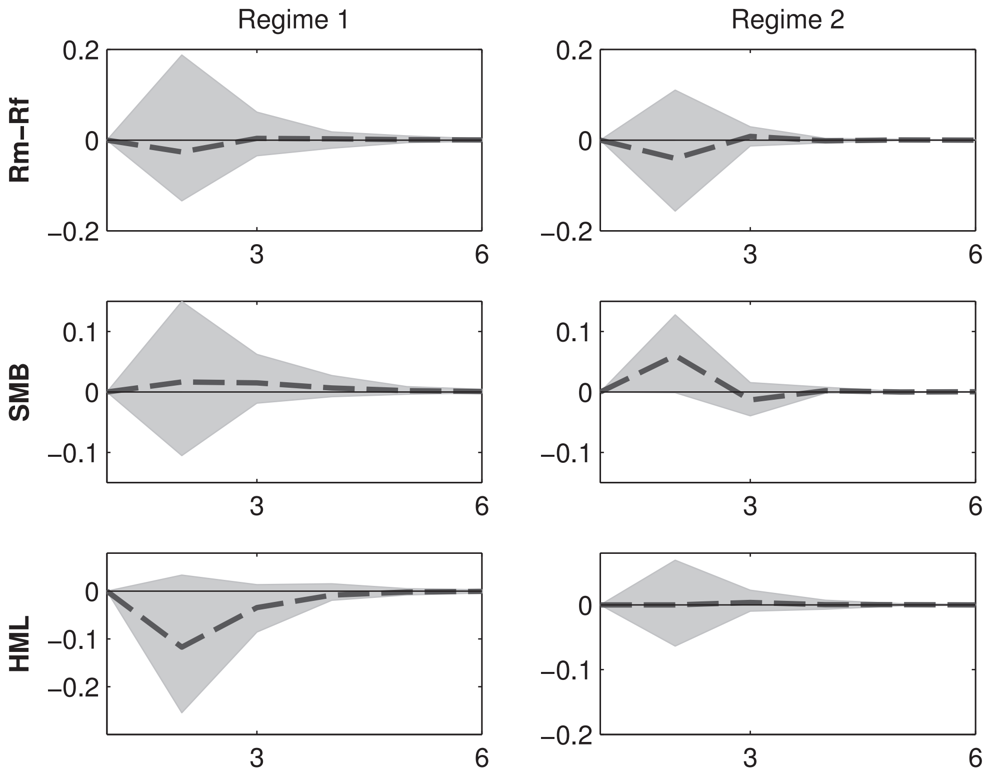
Figure 4 displays a negative effect of ΔEPU on MKT during the high volatility regime, suggesting a negative relationship between the market risk premium and the change in the economic policy uncertainty in high volatility regime. Contrarily to a shock to ΔVXO, the IRFs show a negative effect of a shock to ΔEPU on SMB only during the low volatility regime. This result indicates that investors move to large-cap firms from small-cap firms when the economic policy uncertainty increases in high volatility regime. Finally, the IRFs displays a negative effect of ΔEPU on HML during the high volatility regime, as for ΔVXO, with a longer horizon (5 months), and also during the low volatility regime. Note that

[17]Durand et al. (2011) also find that an effect of VIX is positive on HML but negligible on SMB whereas this effect is negligible on SMB and HML for Shamsuddin and Kim (2014). These authors use the VIX index (in first-difference for Durand et al., 2011; in level for Shamsuddin and Kim, 2014) for market uncertainty while we use the VXO index. Durand et al. (2011) use daily data from February 1, 1993 to July 30, 2007, and Shamsuddin and Kim (2014) employ weekly data from January 1990 to December 2011.

the impact on HML is larger from a shock to ΔVXO (-16.2%) than from a shock to ΔEPU (-4.2%) (see Table 3). Further, the impact of EPU shock on HML is both larger and more persistent during periods when volatility is high as opposed to periods during which volatility is lower. A 1% shock to ΔEPU leads to 4.3% and 1.6% decline of HML during the high and low volatility regime, respectively. This is consistent with investors preferring growth stocks over value stocks when economic policy uncertainty increases.

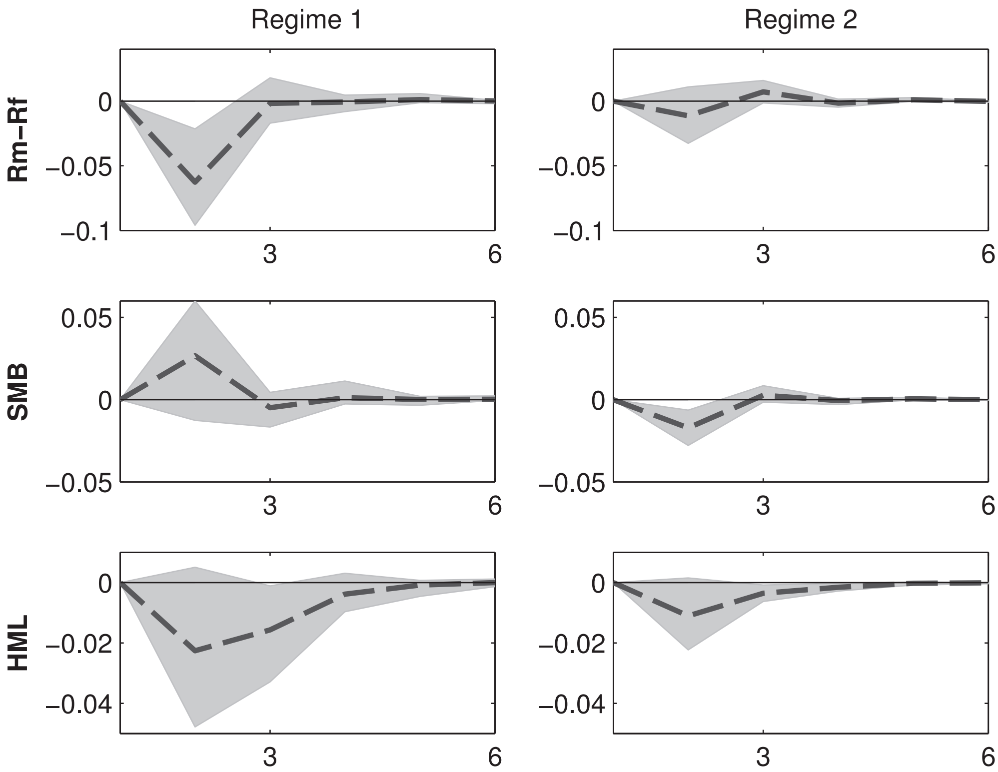
The results presented in Figure 5 show that the risk premia respond to a shock to ΔUMACRO only on MKT during the high volatility regime. This shock has very higher impact (-48.8%) than that from a shock to ΔEPU (-6.4%), and this effect is more persistent. This finding indicates that a negative relationship between the market risk premium and the change in the macroeconomic uncertainty in high volatility regime. However, the change in the macroeconomic uncertainty seems to have no effect on HML and SMB factors.

Figure 3. Response to VXO shock in MSIAH(4)-VAR(1)



Note: Responses of the risk premia (Rm-Rf), SMB and HML to a positive shock to VXO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

Figure 4. Response to EPU shock in MSIAH(4)-VAR(1)



Note: Responses of the risk premia (Rm-Rf), SMB and HML to a positive shock to EPU by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

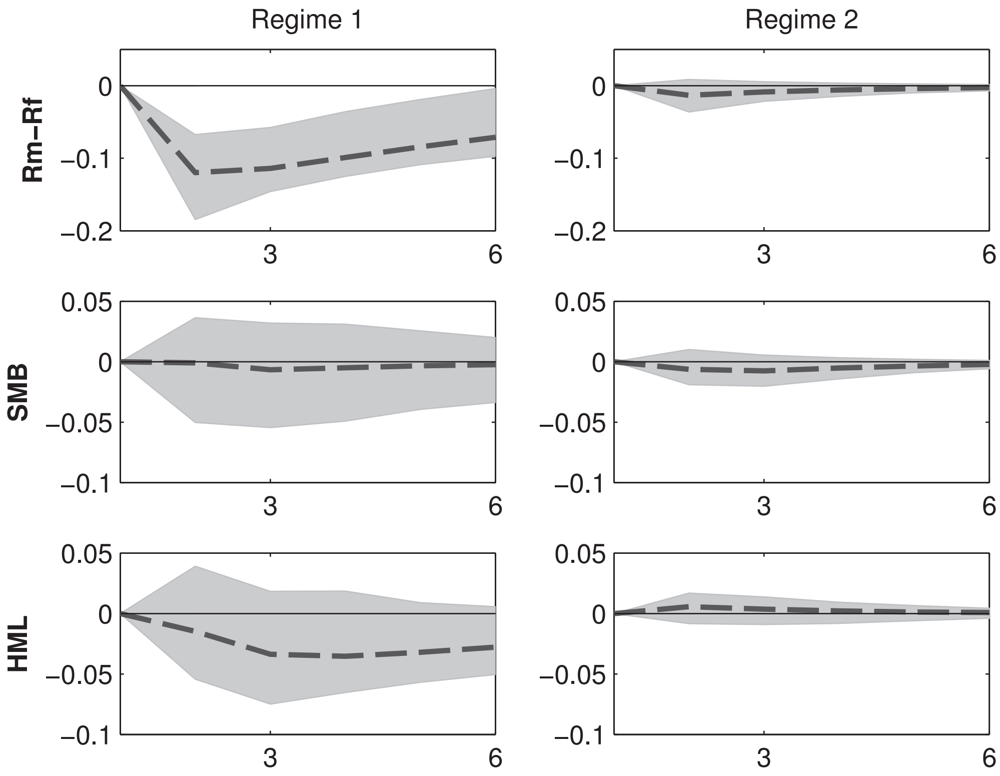
4.2 Economic uncertainty index

Since the three measures of uncertainty are highly positively correlated with each other (Table 2) and they tend to move together, suggesting there is a common uncertainty component to all the measures (Figure 1), we propose an aggregate measure of economic uncertainty (UFACTOR) by using Principal Component Analysis (PCA).[18] We use the PCA to extract the common component of the three uncertainty proxies that capture different dimensions of the economic uncertainty: economic policy, finance and macroeconomics. The first principal component from PCA sufficiently captures the common variation among the three uncertainty measures.

Figure 6 presents the economic uncertainty index obtained from the first principal component of the

[18] Bali et al. (2014) also proposed a newly measure of macroeconomic risk associated to a quantitative indicator of economic uncertainty, using individual measures of macroeconomic risk obtained from estimating time-varying conditional volatility of the economic indicators based on a VAR-GARCH model. Their indicator is computed from January 1994 to March 2012. Haddow et al. (2013) also used PCA to construct an uncertainty index based on four indicators for the UK on the 1985-2013 period.

Figure 5. Response to UMACRO shock in MSIAH(4)-VAR(1)



Note: Responses of the risk premia (Rm-Rf), SMB and HML to a positive shock to UMACRO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

three uncertainty measures. The economic uncertainty index is generally higher during the economic recessions, especially during the 2008 global financial crisis, and also around the October 1987 financial crisis and the LTCM and Russian Debt crisis of 1998. This result is consistent with Bloom et al. (2012) who find that recessions appear in periods of significantly higher economic uncertainty.

Table 4 displays the correlation between the economic uncertainty index and the three uncertainty measures, showing that they are highly correlated. We find similar correlations between the changes in the economic uncertainty index and the Fama-French factors, namely ΔUFACTOR is positively correlated to MKT and SMB, and negatively to HML.

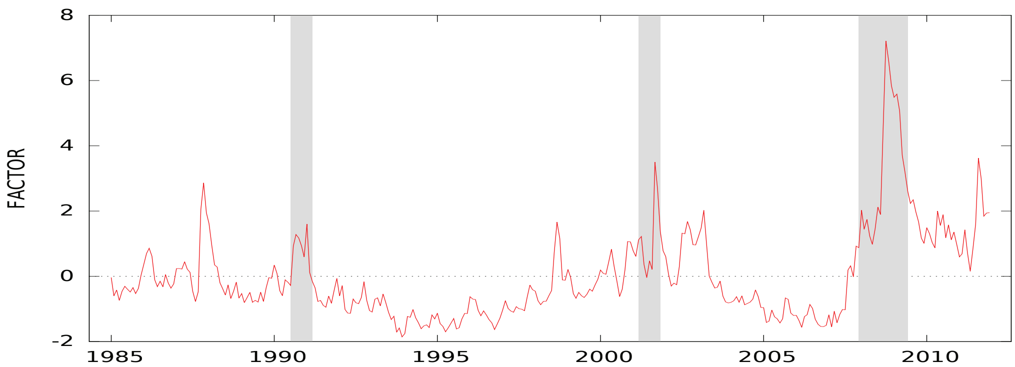
From the MS-VAR model, both regimes are highly persistent according to the transition matrix (Table 6, Appendix A), with transition probabilities lying between 85% and 94% month-to-month probabilities of remaining in the low and high volatility regimes, respectively. The timing of the change across regimes and the number of months for which the economic uncertainty index is under the two regimes are similar to our findings from specific uncertainty measures.

Table 3. Cumulative responses to shocks from period 0 to 6.

Shock \ Response	MKT		SMB		HML	
	High	Low	High	Low	High	Low
ΔVXO	-0.019	-0.033	0.040	0.048	-0.162	0.004
ΔEPU	-0.064	-0.005	0.023	-0.014	-0.043	-0.016
ΔUMACRO	-0.488	-0.034	-0.226	-0.018	-0.068	0.021
ΔUFACTOR3	-1.685	-0.117	0.364	-0.335	-1.312	-0.823

This table reports cumulative responses to different uncertainty shocks to the three Fama-French factors. High and Low denote high and low volatility regimes, respectively.

Figure 6. Economic Uncertainty Index based on 3 uncertainty proxies.



Notes: Shaded regions are NBER recession dates. The data are monthly and span the period 1985:01-2011:12.

Table 4. Correlations.

	ΔVXO	ΔEPU/100	ΔUMACRO/100	ΔUFACTOR3	ΔUFACTOR6
ΔVXO	1.00	0.39	0.25	0.82	0.82
ΔEPU/100		1.00	0.15	0.83	0.71
ΔUMACRO/100			1.00	0.38	0.36
ΔUFACTOR3				1.00	0.93
ΔUFACTOR6					1.00
	MKT	SMB	HML	ΔUFACTOR	ΔUFACTOR6
MKT	1.00	0.19	-0.27	-0.50	-0.51
SMB		1.00	-0.33	-0.23	-0.26
HML			1.00	0.08	0.10
ΔUFACTOR3				1.00	0.93
ΔUFACTOR6					1.00

Figure 8 displays a negative effect of ΔUFACTOR on MKT during the high volatility regime, suggesting a negative relationship between the market risk premium and the change in the economic uncertainty index in high volatility regime. This shock to ΔUFACTOR has a higher effect on MKT than those from ΔEPU and ΔUMACRO, with a short horizon (3 months). The IRFs displays a negative effect of ΔUFACTOR on HML during both volatility regime, as for ΔEPU, with a longer horizon, namely 6 and 5 months, under the high and low regime, respectively, and a higher impact. This suggests that the impact of uncertainty shock on HML is larger during periods when volatility is high as opposed to periods during which volatility is lower. This is consistent with investors preferring growth stocks over value stocks when global uncertainty increases.

Figure 7. Estimated smoothed probabilities for MSIAH(4)-VAR(1): UFACTOR

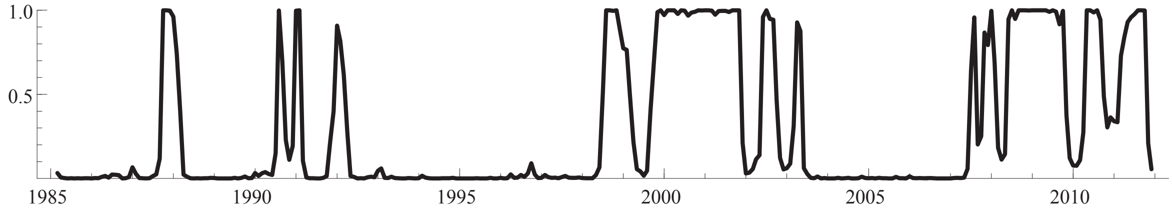
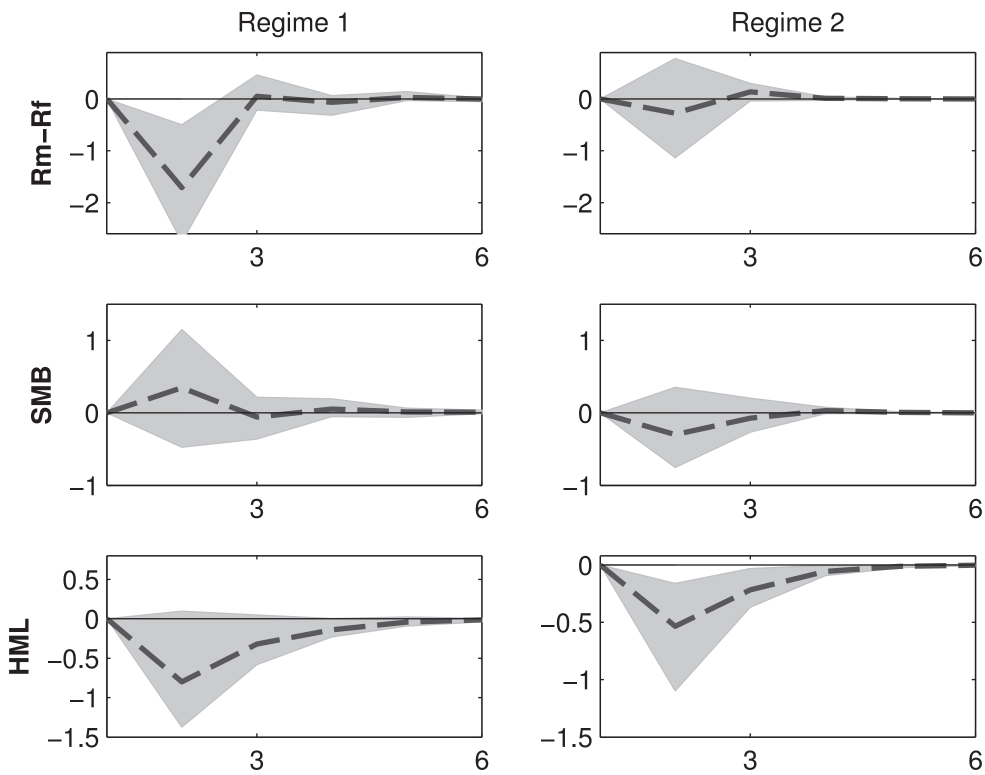


Figure 8. Response to UFACTOR shock in MSIAH(4)-VAR(1)



Note: Responses of the risk premia (Rm-Rf), SMB and HML to a positive shock to UFACTOR by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

4.3 Robustness check

4.3.1 Momentum and Liquidity Factors

As robustness check of our results on IRFs from the MSIAH(4)-VAR(1) models with the different measures of uncertainty, we add two others risk factors with (i) the momentum factor (Winner Minus Loser, WML) introduced by Cahart (1997), and (ii) the aggregate liquidity factor (LIQ) proposed by Pastor and Stambaugh (2003). Cahart (1997) proposes a four-factor model by adding this risk factor into the Fama-French three-factor model. The phenomenon of price momentum is documented in several studies (see, e.g., Jegadeesh and Titman, 1993; Chan et al., 1996; Fama and French, 1996; Jegadeesh and Titman, 2001), and a number of studies show that liquidity-related risks are prices (see, e.g., Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Korajczyk and Sadkha, 2008; Lee, 2011). The data for WML and LIQ comes from Kenneth French's website and from Lubos Pastor's website, respectively (Figure 12).[19]. We obtain the same results from the MSIAH(5)-VAR(1) model than from the MSIAH(4)-VAR(1) models for (i) the both highly persistent regimes with the same timing of the change across regimes and with slightly higher number of months for which the regime remains in the low or high volatility regimes (Figure 14); (ii) the effects of a shock to uncertainty on risk premia (MKT, HML and SMB) (Figure 15). These findings show the robustness of our results according to the number of variables in the MS-VAR model.

More interesting, Figure **??** reports a short negative effect of ΔVXO on WML only during the high volatility regime, whereas we find a positive effect of ΔEPU (Figure **??**) and ΔUMACRO (Figure Figure **??**) on the momentum premium, especially a highly persistent effect from a shock of macroeconomic uncertainty.[20] These results suggest that investors appear to move to proven stocks (past winners) rather than "glamor" stocks when economic policy and macroeconomic uncertainties increase or when market uncertainty decreases during the high volatility regime.

Further, Figure 15 displays a positive effect of ΔVXO on liquidity factor during the high volatility regime, with a short horizon (2 months), suggesting that investors preferring liquidity stocks when market uncertainty increases. This finding is consistent with the flight-to-liquidity phenomenon where

[19] The data are available on http://faculty.chicagobooth.edu/lubos.pastor/research/.

[20] Information uncertainty has been proposed as an explanation for the abnormal returns earned via momentum strategies. Faced with greater uncertainty, investors are increasingly unable to accurately determine the true value of an asset and are more likely to misprice it. Zhang (2006) finds that information uncertainty exacerbates momentum, using forecast dispersion as a measure of information uncertainty, whereas Verardo (2009) shows that investor uncertainty, based on company's fundamentals, is associated with less momentum. Note that Durand et al. (2011) and Kim and Shamsuddin (2014) find that WML responds positively to a shock in VIX.

investors rebalance their portfolios toward more liquid assets. This is also consistent with Chung and Chuwonganant (2014) who found that market uncertainty (measured by the VIX) exerts a large market-wide impact on liquidity. We find the same result with a shock of ΔEPU (Figure 16).[21]

4.3.2 PCA from 6 uncertainty measures

As robustness check of our results on the aggregate measure of economic uncertainty, we consider three others proxies of uncertainty measure to construct the economic uncertainty index in our sample. In this respect, we use a measure of equity market uncertainty with the equity market-related economic uncertainty (EMEU) proposed by Baker et al. (2013), a measure of financial uncertainty with the corporate bond spreads (SPREAD), defined as the monthly spread of the 30-year Baa-rated corporate bond yield index over the 30-year treasury bond yield, and a measure of (micro)economic (firm-specific) uncertainty with the forecast disagreement index (FDISP) based on the forecast dispersion in the general business situation question from the Business Outlook Survey proposed by Bachmann et al. (2013).[22] These uncertainty measures are significantly correlated with the three previous measures, except for FDISP (Table 5).

Table 5. Correlations.

	ΔVXO	ΔEPU/100	ΔUMACRO/100	ΔSPREAD	ΔEMEU	ΔFDISP	ΔUFACTOR6
ΔVXO	1.00	0.39	0.25	0.45	0.51	0.07	0.82
ΔEPU/100		1.00	0.15	0.07	0.54	0.02	0.71
ΔUMACRO/100			1.00	0.29	0.16	0.03	0.36
ΔSPREAD				1.00	0.12	0.10	0.49
ΔEMEU					1.00	0.02	0.77
ΔFDISP						1.00	0.25
ΔUFACTOR6							1.00

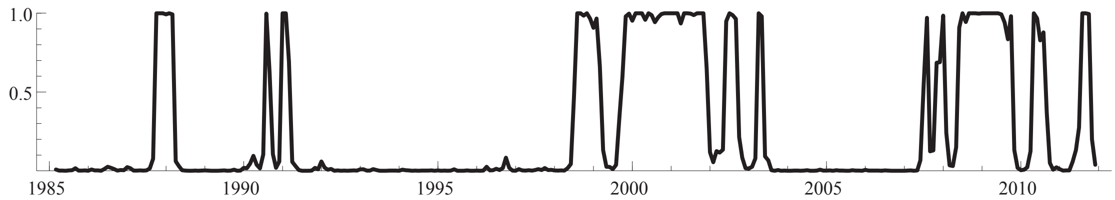
The economic uncertainty index is obtained by extracting the common component of the six uncertainty proxies. Figure 13 presents the economic uncertainty index obtained from six uncertainty measures (UFACTOR6) and also that obtained from three measures (UFACTOR3). The evolution of both uncertainty indexes are very similar. Further, they are highly correlated (0.93, Table 4).

We find the same results from this economic uncertainty index than from the economic uncertainty

[21] We obtained the same results for a shock of ΔUMACRO and ΔUFACTOR on the three Fama-French factors from the MSIAH(4)-VAR(1) and MSIAH(5)-VAR(1) models (see Technical Appendix). However, the responses to ΔUMACRO and ΔUFACTOR on the liquidity factor are non significant.

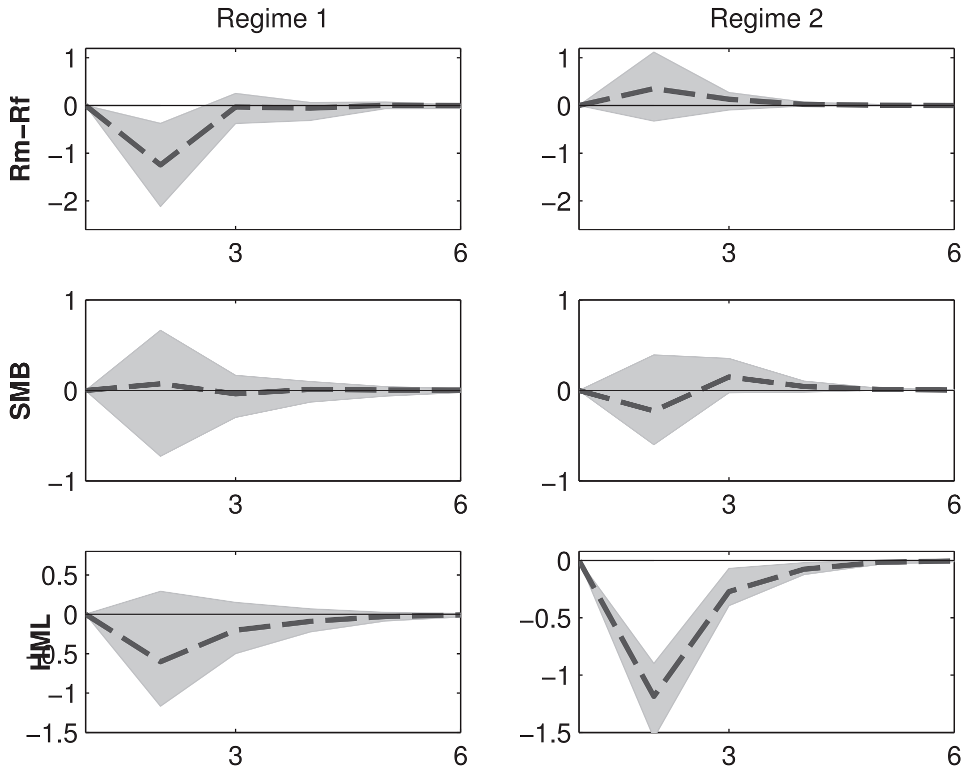
[22] There are others proxies of uncertainty but they are not available on our sample.

Figure 9. Estimated smoothed probabilities for MSIAH(4)-VAR(1): UFACTOR6



index extracted from three measures for the high and low volatility regimes (Figure **??**) and the responses to an aggregate economic uncertainty shock on the three risk premia (Figure 10). These findings show the robustness of our results on a shock of the economic uncertainty index on the MKT, SMB and HML factors, whatever the uncertainty measures included in the index.

Figure 10. Response to UFACTOR6 shock in MSIAH(4)-VAR(1)



Note: Responses of the risk premia (Rm-Rf), SMB and HML to a positive shock to UFACTOR6 by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

4.3.3 Fama-French portfolios

We study the effect of uncertainty on the 6 Fama-French benchmark portfolios formed on Size and Book-to-Market: small value (SV), small neutral (SN), small growth (SG), big value (BV), big neutral (BN), and big growth (BG). These portfolios, which are constructed at the end of each June, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in $t-1$ divided by ME for December of $t-1$. The BE/ME breakpoints are the 30th and 70th NYSE percentiles.

Figure 22 displays the IRFs for the 6 portfolios. The results show that a negative effect of ΔUFACTOR6 on 4 portfolios (SG, SN, SV and BV) during the high volatility regime, suggesting a negative relationship between these portfolios and the change in the economic uncertainty index in high volatility regime. This is consistent with the view that the small firms are more sensitive of uncertainty in bad times (high volatility). This shock to ΔUFACTOR6 has a higher effect on SG and SV portfolios than for SN and BV portfolios. The uncertainty shock have no effect on BG uncertainty, suggesting that big growth firms are not affected by economic uncertainty shock, even during high volatility regime. This is consistent with investors preferring growth stocks when economic uncertainty increases. Finally, We only find a negative effect of ΔUFACTOR6 on BN portfolio during the low volatility regime.

5 Conclusion

This paper analyzed the sensitivity of the three Fama-French factors in relation to the US economic uncertainty, by using three proxies of uncertainty measures in macroeconomics, financial markets or economic policy. We examined the extent, speed and duration of response of the three risk premia to movements in the US uncertainties under low and high volatility regimes through the MS-VAR model.

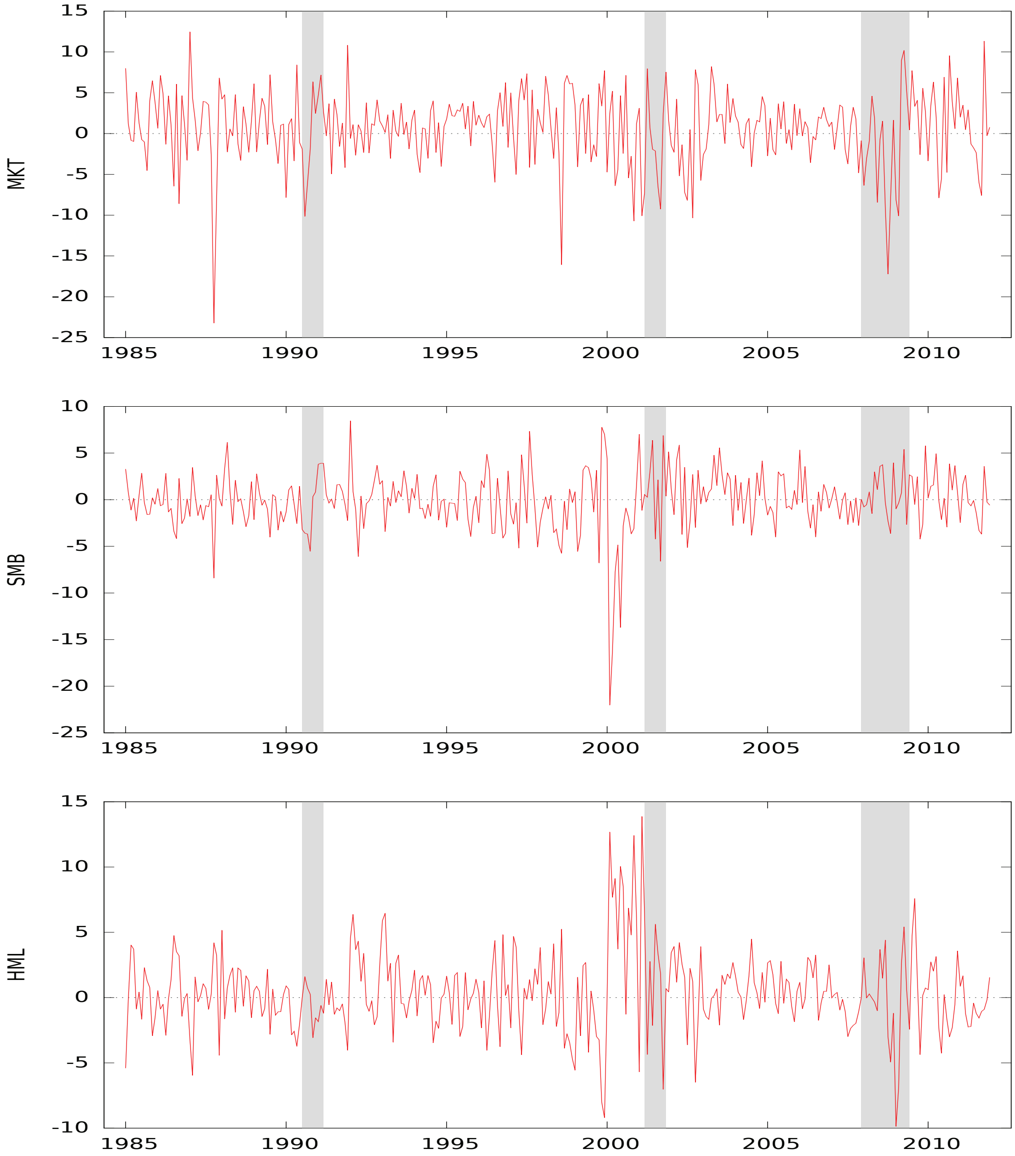
We found clearly two different volatility regimes, where each regime is highly persistent. The first regime, corresponding to the high volatility regime, is the prevailing regime between periods of 2000 to 2003, and 2008 to the end of 2012. These periods correspond to the bear market following the burst of the dot-com bubble and FedŠs interventions, and the 2007-08 financial crisis and the related recession, respectively. The low volatility regime coincides with the two bull market periods; the first was part of the dot-com bubble and the second corresponds to the mortgage market bubble.

Examining the sensitivity of three risk premia (market, size and value) to changes in macroeconomics, financial markets or economic policy uncertainties under low and high volatility regimes, we showed a negative effect of changes in financial and economic policy uncertainties on value risk premia during the high volatility regime. This finding implies that investors move to growth stocks from value stocks in high volatility regime when volatility is expected to increase. The latter suggests that value firms can be more risky than growth firms during high volatility periods. This is consistent with the view that value is riskier than growth in bad times when the price of risk is high (e.g., Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001b; Petkova and Zhang, 2005; Zhang, 2005; Chen et al., 2008).

Finally, we proposed an aggregate measure of economic uncertainty by using Principal Component Analysis based on the three uncertainty proxies. The results on value risk premia are confirmed. We also found a negative relationship between the market risk premium and the change in the economic uncertainty index in high volatility regime.

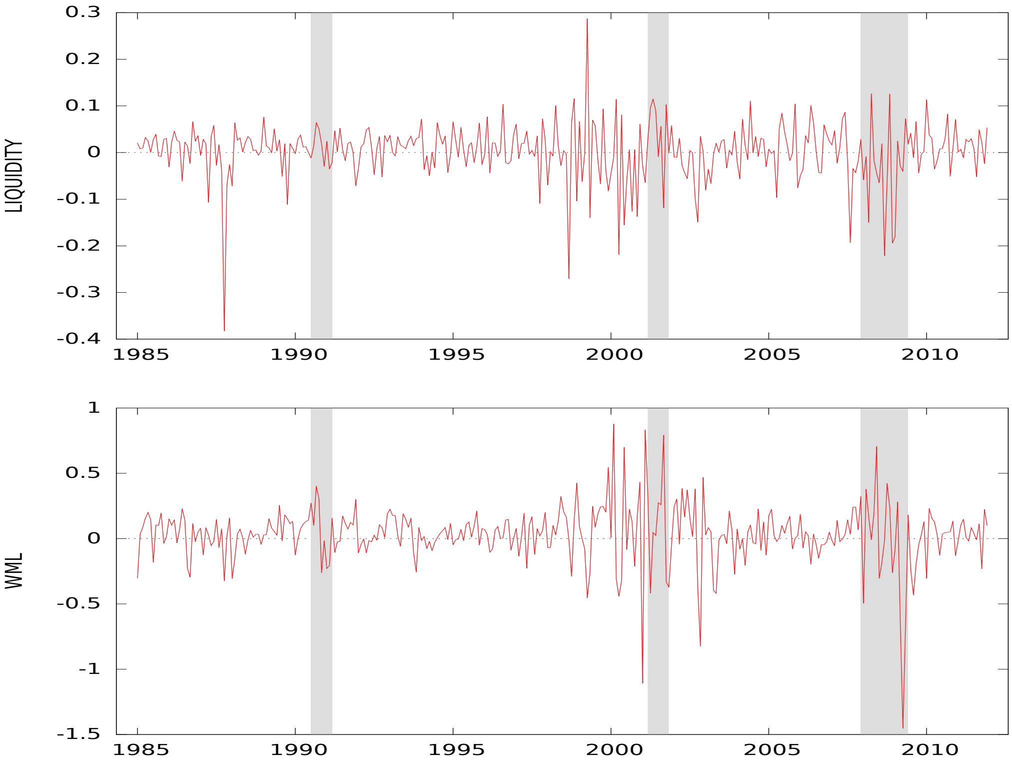
Overall, the results of our analysis point to the sensitivity of US market and value risk premia to economic uncertainty shock, especially during high volatility period, and warrants further research.

Figure 11. Market, size and value risk premia.



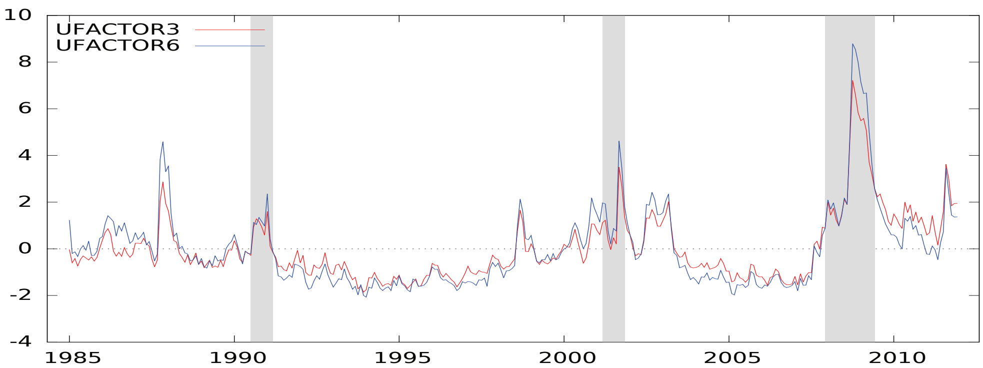
Notes: Shaded regions are NBER recession dates. The data are monthly and span the period 1985:01-2011:12.

Figure 12. Momentum and liquidity factors.



Notes: Shaded regions are NBER recession dates. The data are monthly and span the period 1985:01-2011:12.

Figure 13. Economic Uncertainty Index based on 6 uncertainty proxies.



Notes: Shaded regions are NBER recession dates. The data are monthly and span the period 1985:01-2011:12.

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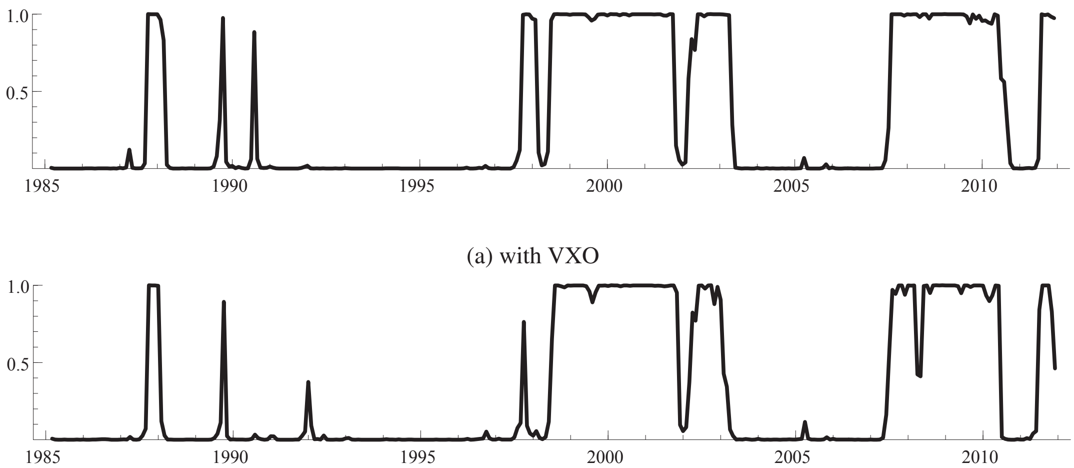
6 Appendix A: MSIAH(4)-VAR models

Table 6. Transition matrix for MSIAH(4)-VAR models

		Regime 1	Regime 2
VXO	Regime 1	0.8775	0.1225
	Regime 2	0.0351	0.9649
UMACRO	Regime 1	0.8788	0.1212
	Regime 2	0.0282	0.9718
EPU	Regime 1	0.8926	0.1074
	Regime 2	0.0378	0.9622
UFACTOR	Regime 1	0,8532	0,1468
	Regime 2	0,0597	0,9403

7 Appendix B: MSIAH(5)-VAR models with liquidity factor

Figure 14. Estimated smoothed probabilities for MSIAH(5)-VAR(1) models with liquidity factor.

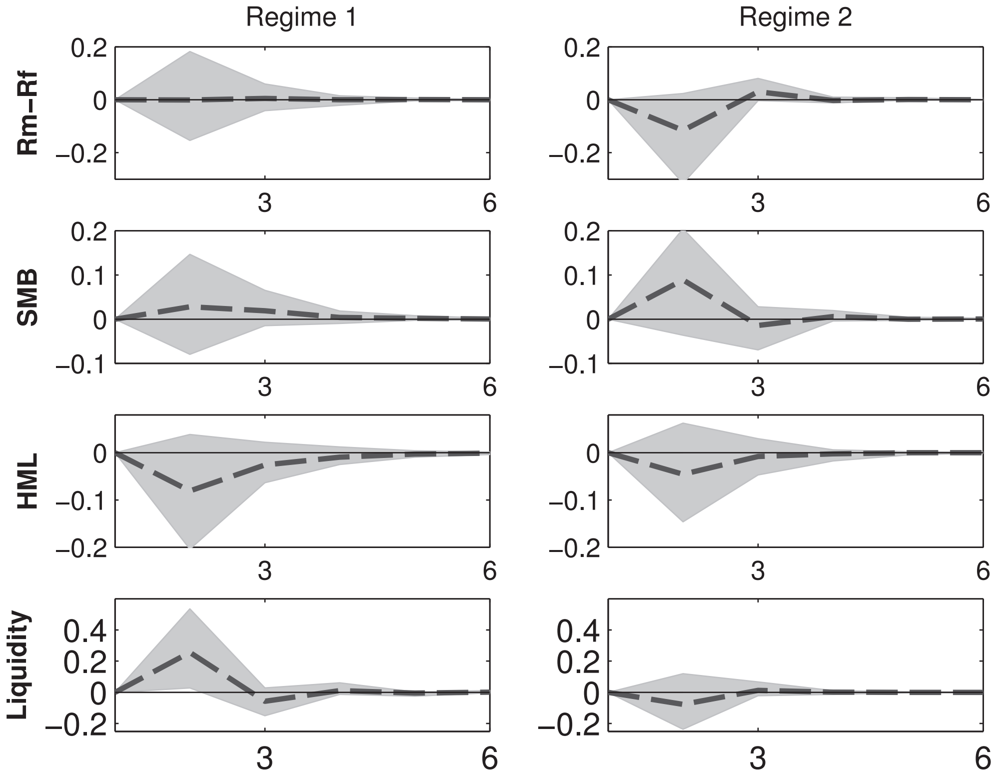


(a) with VXO

(b) with EPU

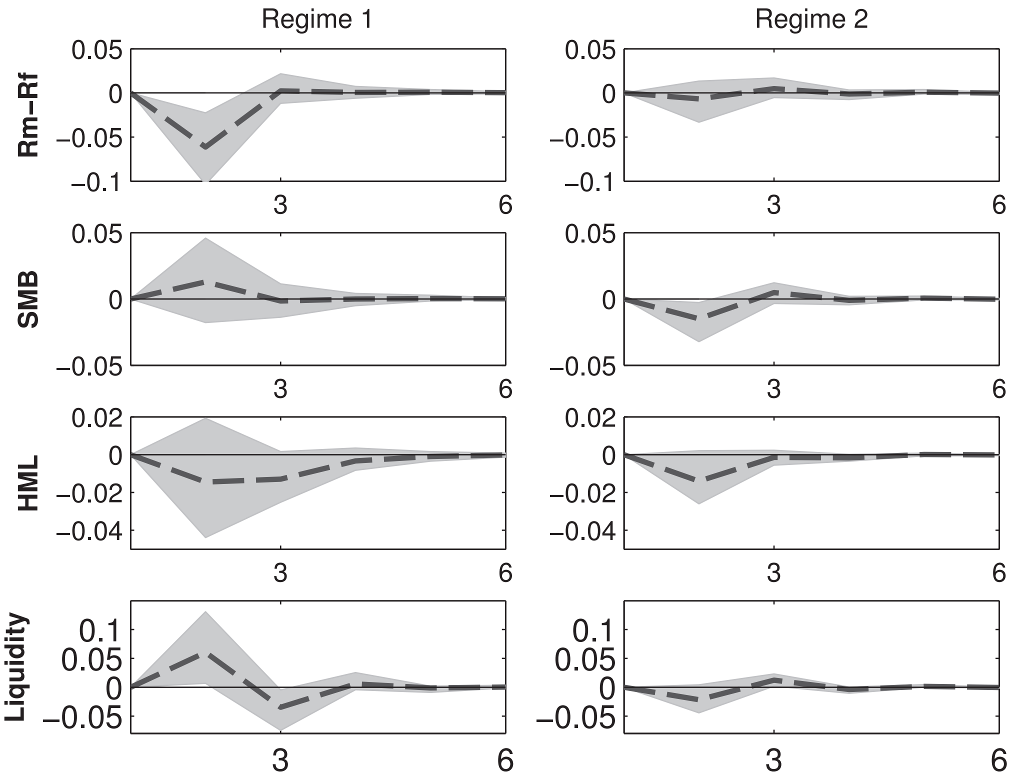
Note: the timeline of the figure indicates two regimes describing the sample period for different models. Regime 1, corresponding to the high volatility regime, is represented over periods of 2000 to 2003, and 2008 to the end of 2012.

Figure 15. Response to VXO shock in MSIAH(5)-VAR(1)



Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to VXO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

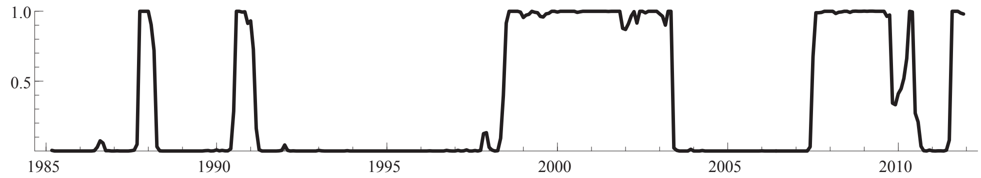
Figure 16. Response to EPU shock in MSIAH(5)-VAR(1)



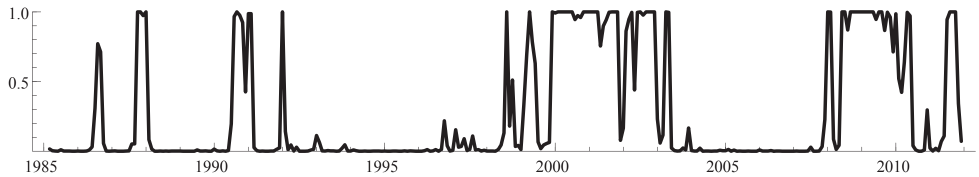
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to EPU by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

8 Appendix C: MSIAH(5)-VAR model with momentum factor

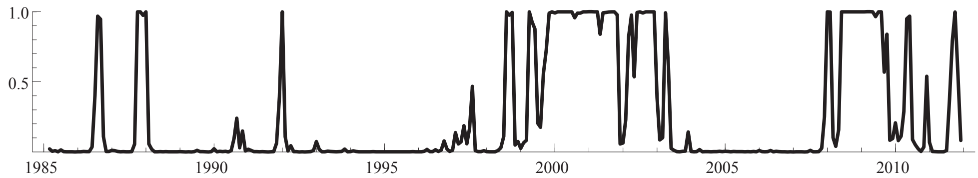
Figure 17. Estimated smoothed probabilities for MSIAH(5)-VAR(1) models with momentum factor.



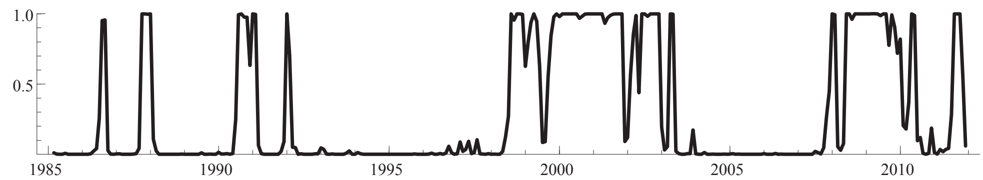
(a) With VXO



(b) With EPU



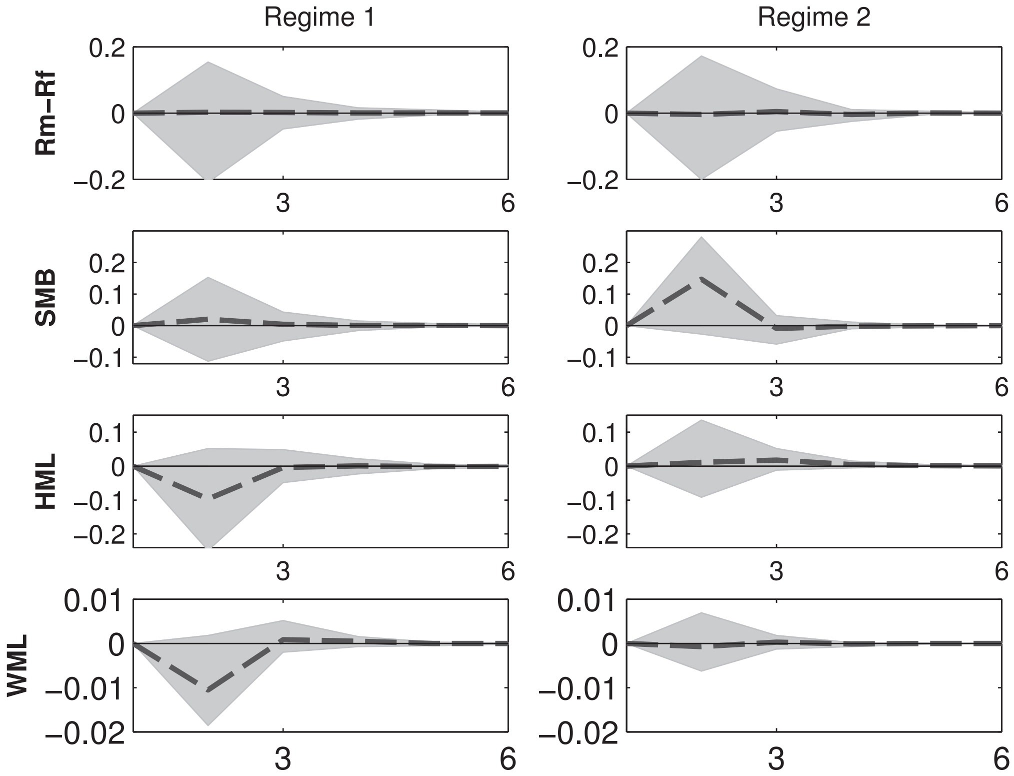
(c) With UMACRO



(d) With Factor 3

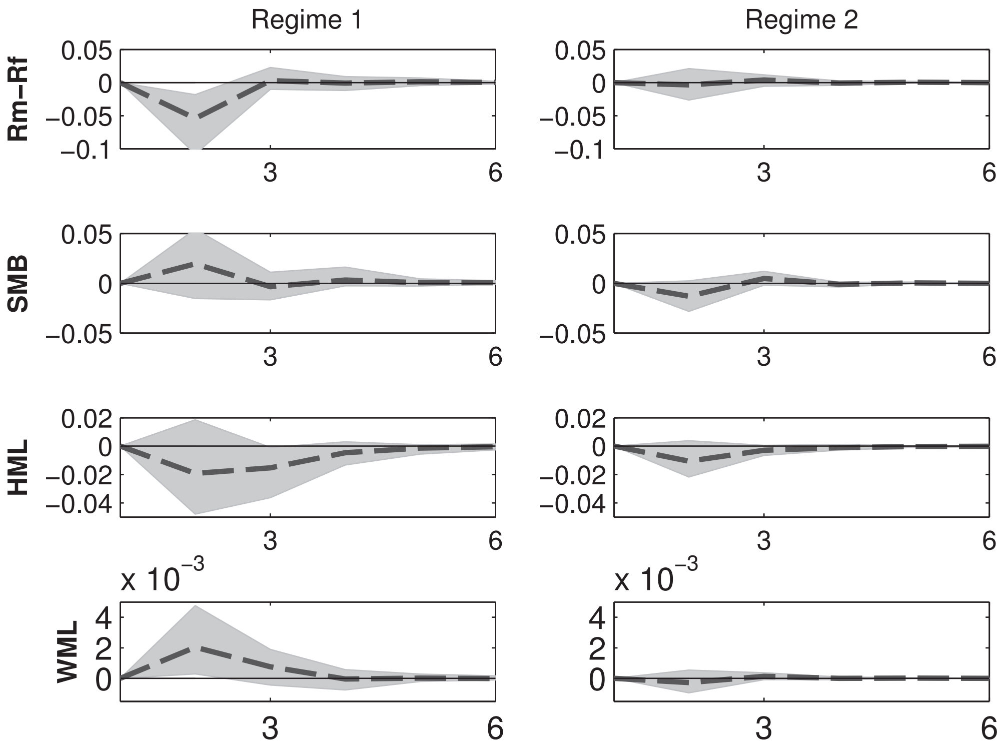
Note: the timeline of the figure indicates two regimes describing the sample period for different models. Regime 1, corresponding to the high volatility regime, is represented over periods of 2000 to 2003, and 2008 to the end of 2012. For different estimations, MSIAH(5)-VAR(1) models contain the four risk premia (Rm-Rf), SMB, HML and WML along with one of the uncertainty factors, namely, VXO, EPU, UMACRO and Factor 3.

Figure 18. Response to VXO shock



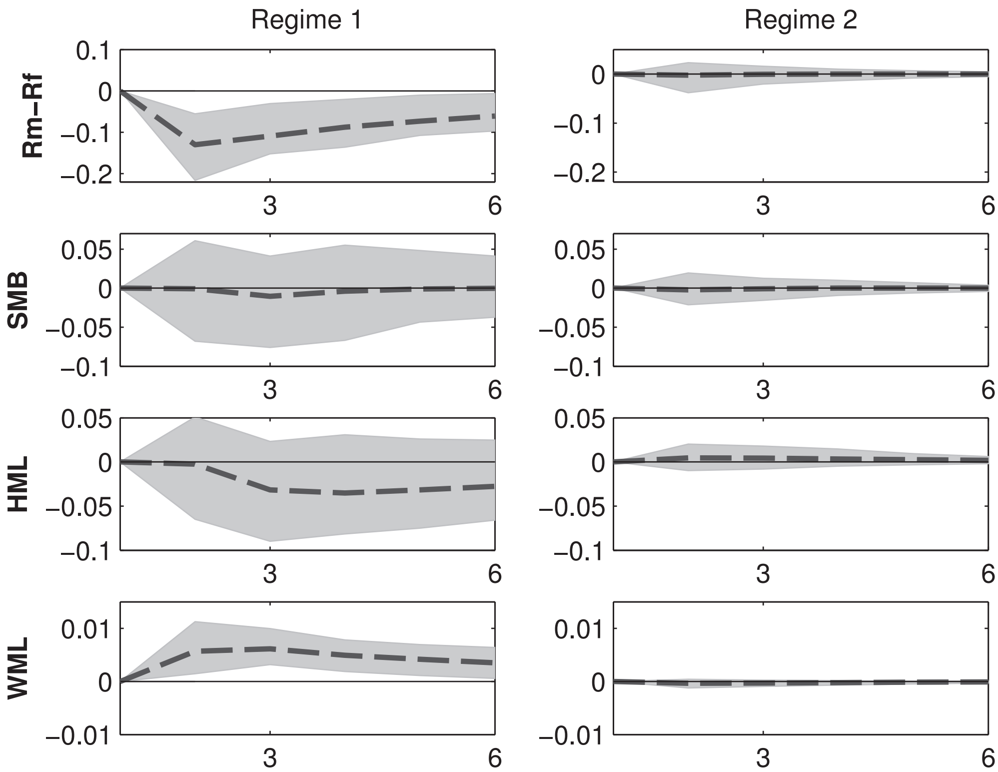
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to VXO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

Figure 19. Response to EPU shock



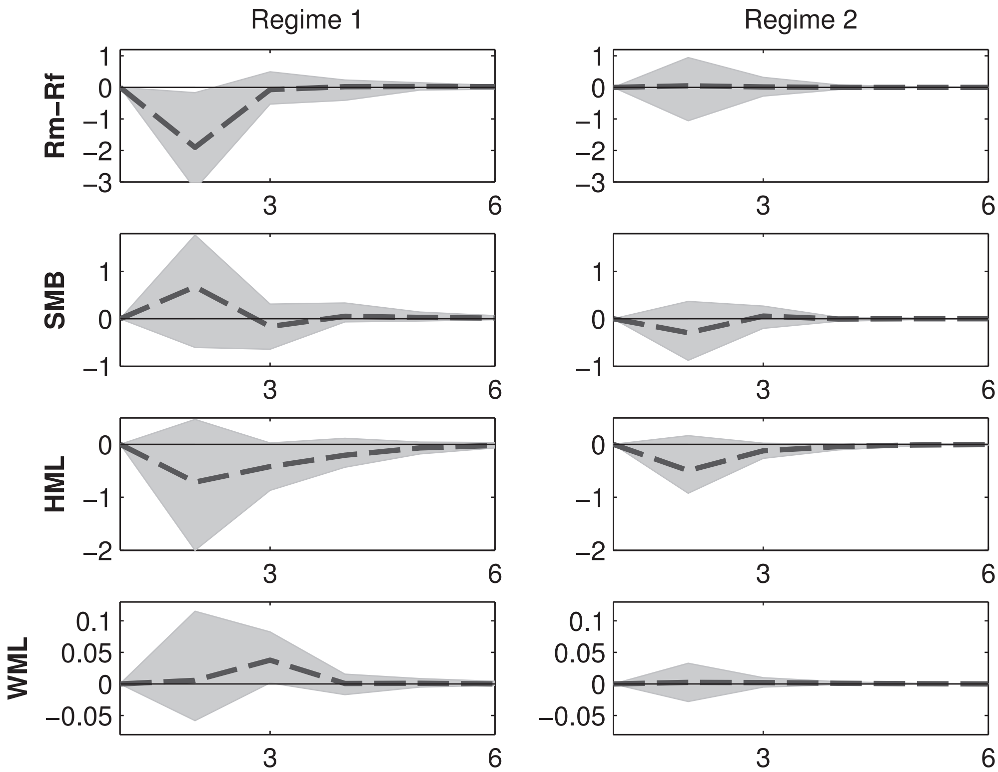
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to EPU by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

Figure 20. Response to UMACRO shock



Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to VXO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

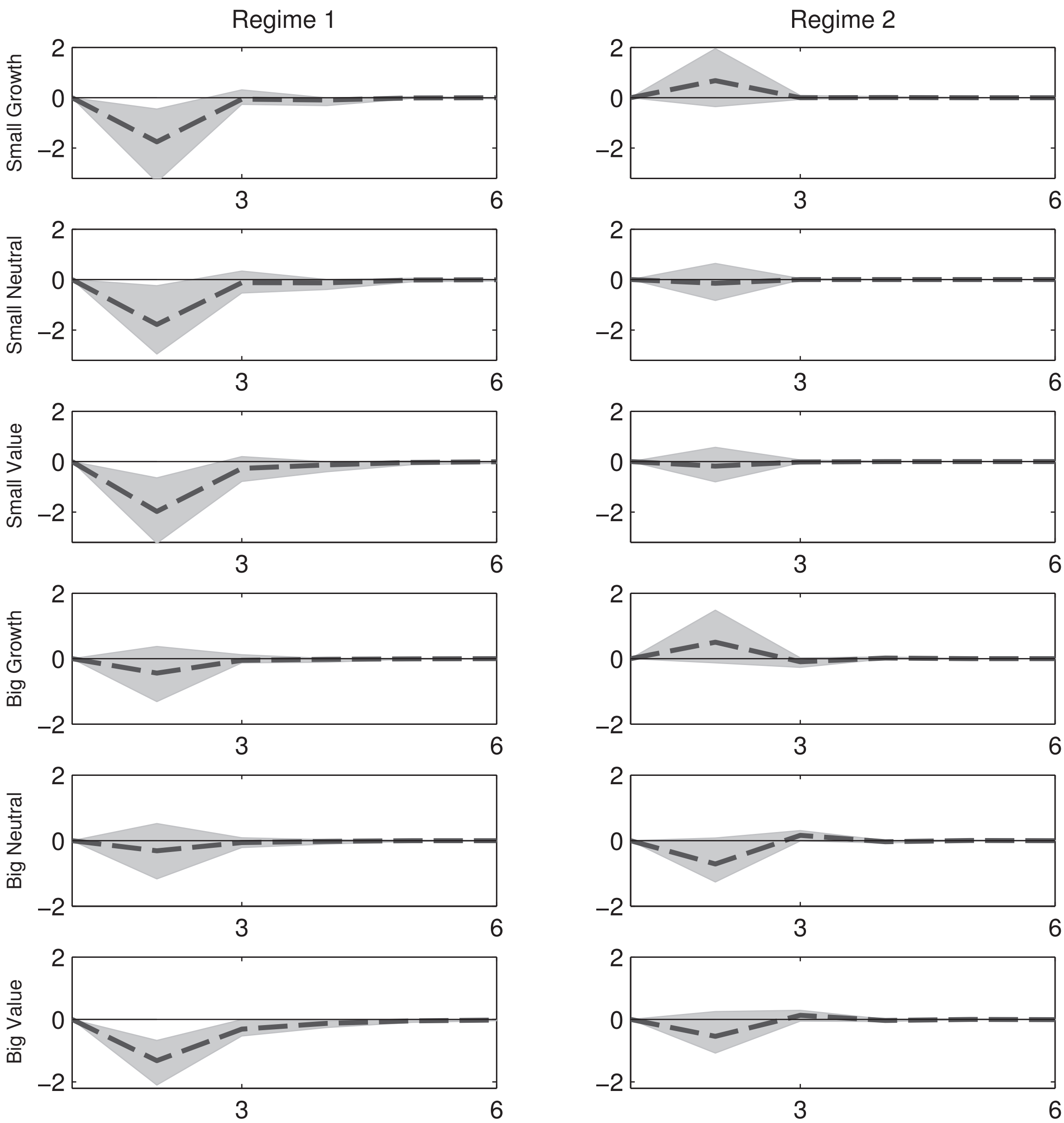
Figure 21. Response to Factor 3 shock



Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to EPU by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

9 Appendix D: MSIAH(6)-VAR model with Fama-French portfolios

Figure 22. Response to UFACTOR6 shock in MSIAH(6)-VAR(1)



Note: Responses of the different portfolios to a positive shock to UFACTOR6 by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

The sensitivity of Fama-French factors to economic uncertainty

Online Technical Appendix

Abstract

This paper analyzes the sensitivity of the three Fama-French factors in relation to the US economic uncertainty, by using three proxies of uncertainty measures in macroeconomics, financial markets or economic policy from January 1985 to December 2011. We examine the extent, speed and duration of response of the three (market, size and value) risk premia to movements in the US uncertainties under low and high volatility regimes through the Markov-regime switching VAR model. We find clearly two (high and low) volatility regimes, where each regime is highly persistent. The high volatility regime is the prevailing regime between periods of 2000 to 2003, and 2008 to the end of 2012. We show a negative effect of changes in financial and economic policy uncertainties on value risk premia during the high volatility regime. This finding imply that investors move to growth stocks from value stocks in high volatility regime when volatility is expected to increase. The latter suggests that value firms can be more risky than growth firms during high volatility periods. We also propose an aggregate measure of economic uncertainty by using Principal Component Analysis based on the three uncertainty proxies. The results on value risk premia are confirmed. We find a negative relationship between the market risk premium and the change in the economic uncertainty index in high volatility regime. Finally, by adding a liquidity risk factor we find a positive effect of financial uncertainty on liquidity factor during the high volatility regime, suggesting that investors preferring liquidity stocks when market uncertainty increases.

Keywords: Fama-French factors; Economic uncertainty; Markov-switching model.

JEL Classification: G10; G11; C32.

1 Appendix A: MSIAH(4)-VAR models

1.1 MSIAH(4)-VAR(p) estimation results: VXO

Table 1. Linearity test: VAR model

Lags	IC	Two regimes[a]	single regime
Lag1	AIC	20.1921*	21.1228
	HQ	20.4823 *	21.2632
	SC	20.9189*	21.4745
Lag2	AIC	20.3035*	21.1397
	HQ	20.7445*	21.3555
	SC	21.4079*	21.6802
Lag3	AIC	20.3558*	21.0405
	HQ	20.9483*	21.3321
	SC	21.8396*	21.7707

[a]All information criterion (values with an asterisk (*)) for all number of lags support the presence of regime shifts.

Table 2. Lag length test: MSIAH(4)-VAR(p) model

	AIC[a]	HQ	SC
Lag = 1	20.1660*	20.3813*	20.7053*
Lag = 2	20.1940	20.4848	20.9224
Lag = 3	20.1991	20.5659	21.1177

[a]The lag length supported by the IC (values with an asterisk (*)) is one.

Table 3. Transition matrix

	Regime 1[a]	Regime 2
Regime 1	0.8775	0.1225
Regime 2	0.0351	0.9649

[a]Note that $p_{i,j} = Pr(s_{t+1} = j | s_t = i)$

1.2 MSIAH(4)-VAR(p) estimation results: UMACRO

Table 4. Linearity test: VAR model

Lags	IC	Two regimes[a]	single regime
Lag1	AIC	13.3697*	13.9413
	HQ	13.6598*	14.0817
	SC	14.0965*	14.2930
Lag2	AIC	13.5314*	13.9615
	HQ	13.9723*	14.1773
	SC	14.6358	14.5020*
Lag3	AIC	13.5449*	13.9674
	HQ	14.1374*	14.2589
	SC	15.0287	14.6975*

[a] All information criterion (values with an asterisk (*)) for all number of lags support the presence of regime shifts (except SC for Lag=2,3).

Table 5. Lag length test: MSIAH(4)-VAR(p) model

	AIC[a]	HQ	SC
Lag = 1	13.3697*	13.6598*	14.0965 *
Lag = 2	13.5314	13.9723	14.6358
Lag = 3	13.5449	14.1374	15.0287

[a]The lag length supported by the IC (values with an asterisk (*)) is one.

Table 6. Transition matrix

	Regime 1[a]	Regime 2
Regime 1	0.8788	0.1212
Regime 2	0.0282	0.9718

[a]Note that $p_{i,j} = Pr(s_{t+1} = j|s_t = i)$

1.3 MSIAH(4)-VAR(p) estimation results: EPU

Table 7. Linearity test: VAR model

Lags	IC	Two regimes[a]	single regime
Lag1	AIC	23.6659*	24.3413
	HQ	23.9561*	24.4817
	SC	24.3927*	24.6929
Lag2	AIC	23.9631*	24.3711
	HQ	24.4041*	24.5869
	SC	25.0675	24.9115*
Lag3	AIC	23.9113*	24.3494
	HQ	24.5038*	24.6410
	SC	25.3950	25.0795*

[a]Information criterion (values with an asterisk (*)) for all number of lags (except SC for Lag=2,3) support the presence of regime shifts.

Table 8. Lag length test: MSIAH(4)-VAR(p) model

	AIC[a]	HQ	SC
Lag = 1	23.6328*	23.8481*	24.1721*
Lag = 2	23.8411	24.1320	24.5696
Lag = 3	23.8345	24.2013	24.7531

[a]The lag length supported by the IC (values with an asterisk (*)) is one.

Table 9. Transition matrix

	Regime 1[a]	Regime 2
Regime 1	0.8926	0.1074
Regime 2	0.0378	0.9622

[a]Note that $p_{i,j} = Pr(s_{t+1} = j|s_t = i)$

1.4 MSIAH(4)-VAR(p) estimation results: UFACTOR

Table 10. Linearity test: VAR model

Lags	IC	Two regimes[a]	single regime
Lag1	AIC	16,32949*	17,1329
	HQ	16,6196*	17,2733
	SC	17,0562*	17,4845
Lag2	AIC	16,5494*	17,1895
	HQ	16,9903*	17,4053
	SC	17,6538*	17,73
Lag3	AIC	16,8641*	17,1853
	HQ	17,4566*	17,4768
	SC	18,3479	17,9154*

[a]Information criterion (values with an asterisk (*)) for all number of lags (except SC for Lag=2,3) support the presence of regime shifts.

Table 11. Lag length test: MSIAH(4)-VAR(p) model

	AIC[a]	HQ	SC
Lag = 1	16,3294*	16,6196*	17,0562*
Lag = 2	16,5494	16,9903	17,6538
Lag = 3	16,8641	17,4566	18,3479

[a]The lag length supported by the IC (values with an asterisk (*)) is one.

Table 12. Transition matrix

	Regime 1[a]	Regime 2
Regime 1	0,8532	0,1468
Regime 2	0,0597	0,9403

[a]Note that $p_{i,j} = Pr(s_{t+1} = j|s_t = i)$

2 Appendix B: MSIAH(5)-VAR models with liquidity factor

2.1 MSIAH(5)-VAR(p) estimation results: VXO

Table 13. Linearity test:VAR model

Lags	IC	Two regimes[a]	single regime
Lag1	AIC	26.4611*	27.7957
	HQ	26.8916*	28.0063
	SC	27.5395*	28.3232
Lag2	AIC	26.5940*	27.7418
	HQ	27.2601*	28.0702
	SC	28.2624*	28.5643
Lag3	AIC	26.6210*	27.6222
	HQ	27.5238*	28.0689
	SC	28.8820	28.7409*

[a]Information criterion (values with an asterisk (*)) for all number of lags (except SC for Lag=2,3) support the presence of regime shifts.

Table 14. Lag length test: MSIAH(5)-VAR(1) model

	AIC[a]	HQ	SC
Lag = 1	26.4611*	26.8916*	27.5395*
Lag = 2	26.5940	27.2601	28.2624
Lag = 3	26.6210	27.5238	28.8820

[a]The lag length supported by the IC (values with an asterisk (*)) is one.

Table 15. Transition matrix

	Regime 1[a]	Regime 2
Regime 1	0.9278	0.0722
Regime 2	0.0406	0.9594

[a]Note that $p_{i,j} = Pr(s_{t+1} = j|s_t = i)$

2.2 MSIAH(5)-VAR(p) estimation results: EPU

Table 16. Linearity test:VAR model

Lags	IC	Two regimes[a]	single regime
Lag1	AIC	30.0264*	31.0436
	HQ	30.4569*	31.2542
	SC	31.1048*	31.5711
Lag2	AIC	30.2903*	31.0579
	HQ	30.9565*	31.3862
	SC	31.9587*	31.8803
Lag3	AIC	30.3923*	31.0152
	HQ	31.2951*	31.4619
	SC	32.6533	32.1339*

[a]Information criterion (values with an asterisk (*)) for all number of lags (except SC for Lag=2,3) support the presence of regime shifts.

Table 17. Lag length test: MSIAH(5)-VAR(1) model

	AIC[a]	HQ	SC
Lag = 1	30.0264*	30.4569*	31.1048*
Lag = 2	30.2903	30.9565	31.9587
Lag = 3	30.3923	31.2951	32.6533

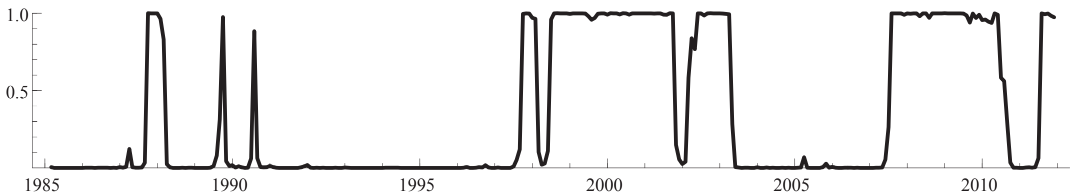
[a]The lag length supported by the IC (values with an asterisk (*)) is one.

Table 18. Transition matrix

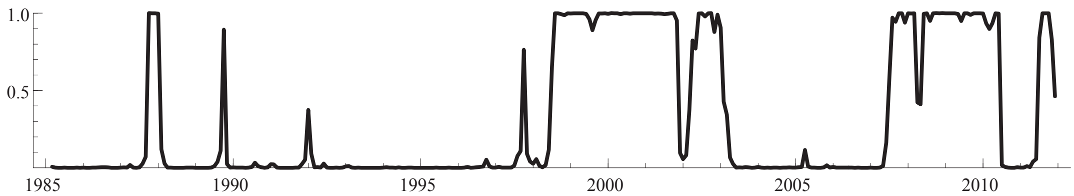
	Regime 1[a]	Regime 2
Regime 1	0.9130	0.0870
Regime 2	0.0396	0.9604

[a]Note that $p_{i,j} = Pr(s_{t+1} = j|s_t = i)$

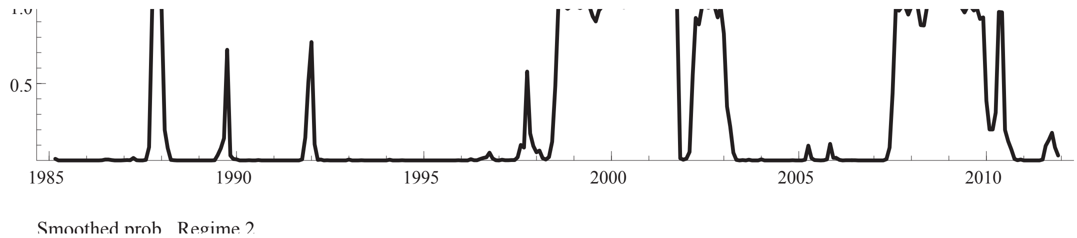
Figure 1. Estimated smoothed probabilities for MSIAH(5)-VAR(1) models with liquidity factor.



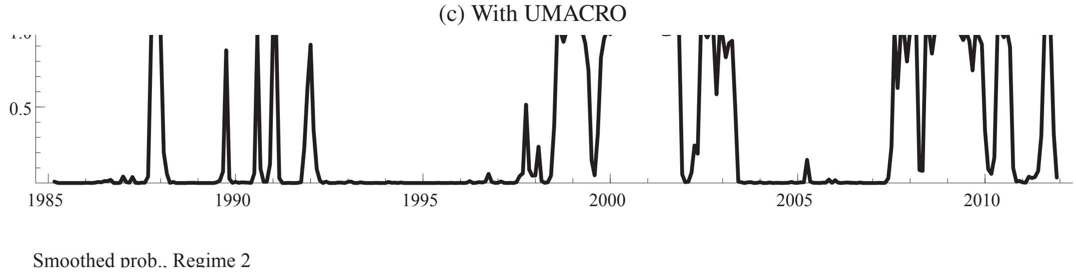
(a) with VXO



(b) with EPU



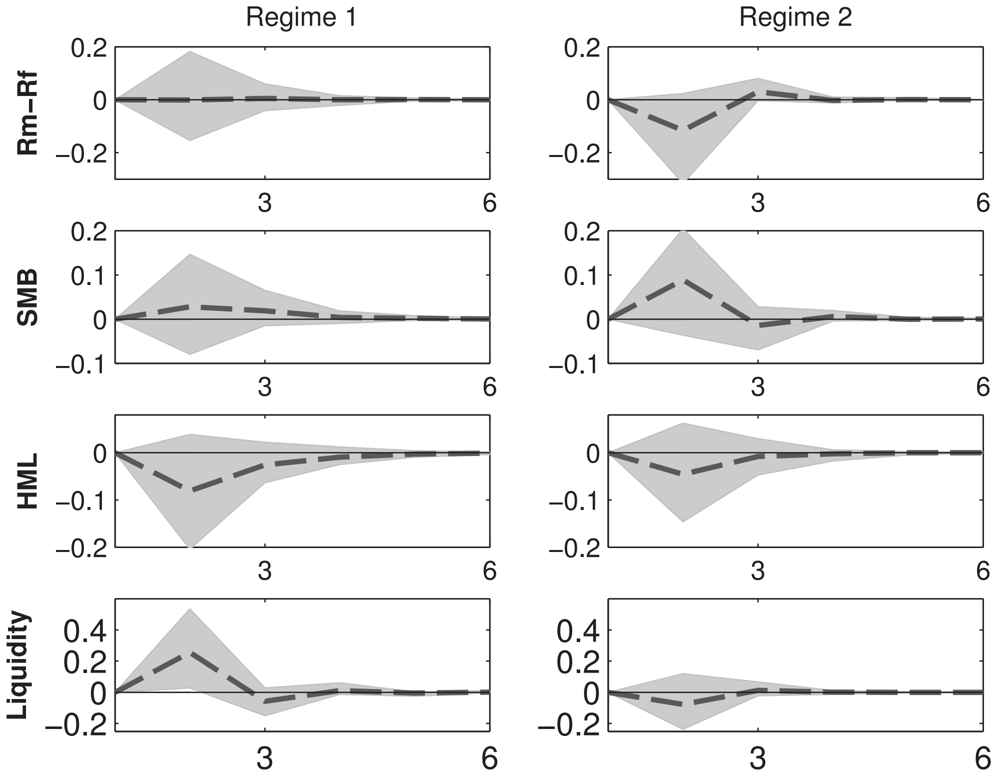
(c) With UMACRO



(d) With Factor 3

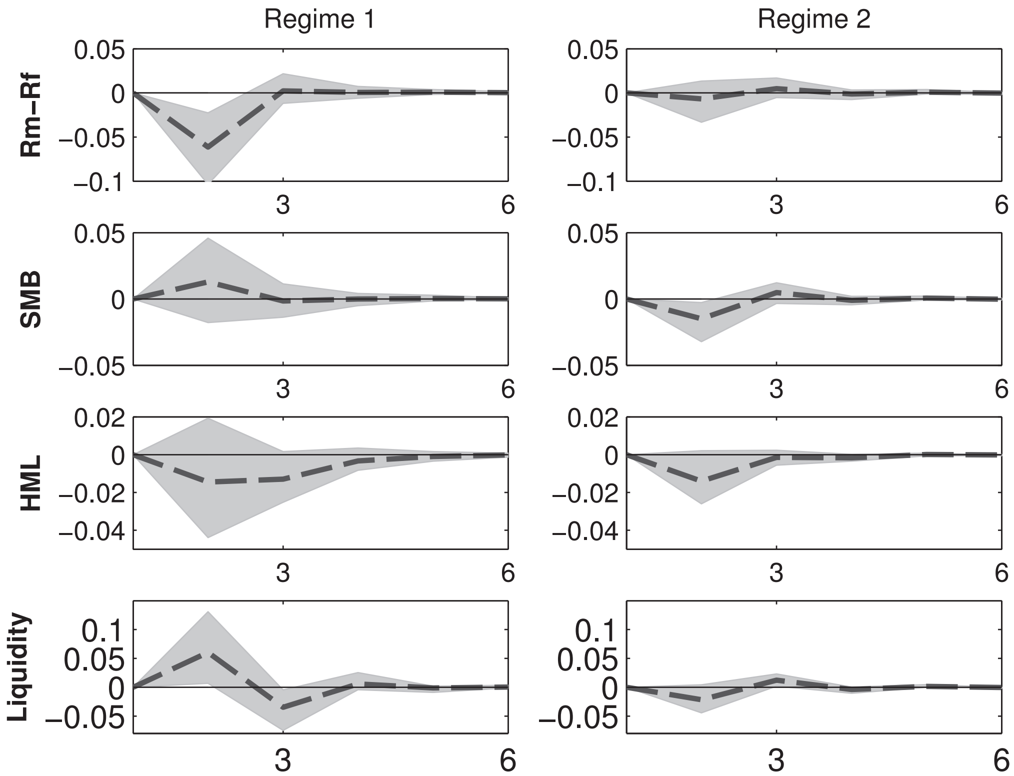
Note: the timeline of the figure indicates two regimes describing the sample period for different models. Regime 1, corresponding to the high volatility regime, is represented over periods of 2000 to 2003, and 2008 to the end of 2012.

Figure 2. Response to VXO shock in MSIAH(5)-VAR(1)



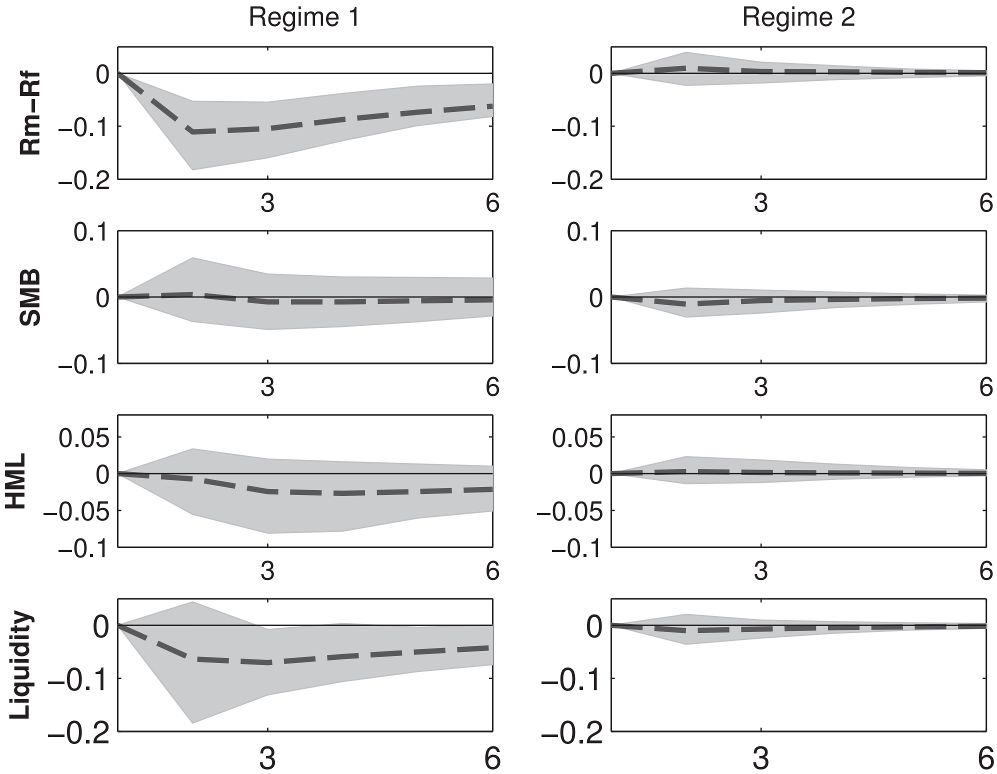
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to VXO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

Figure 3. Response to EPU shock in MSIAH(5)-VAR(1)



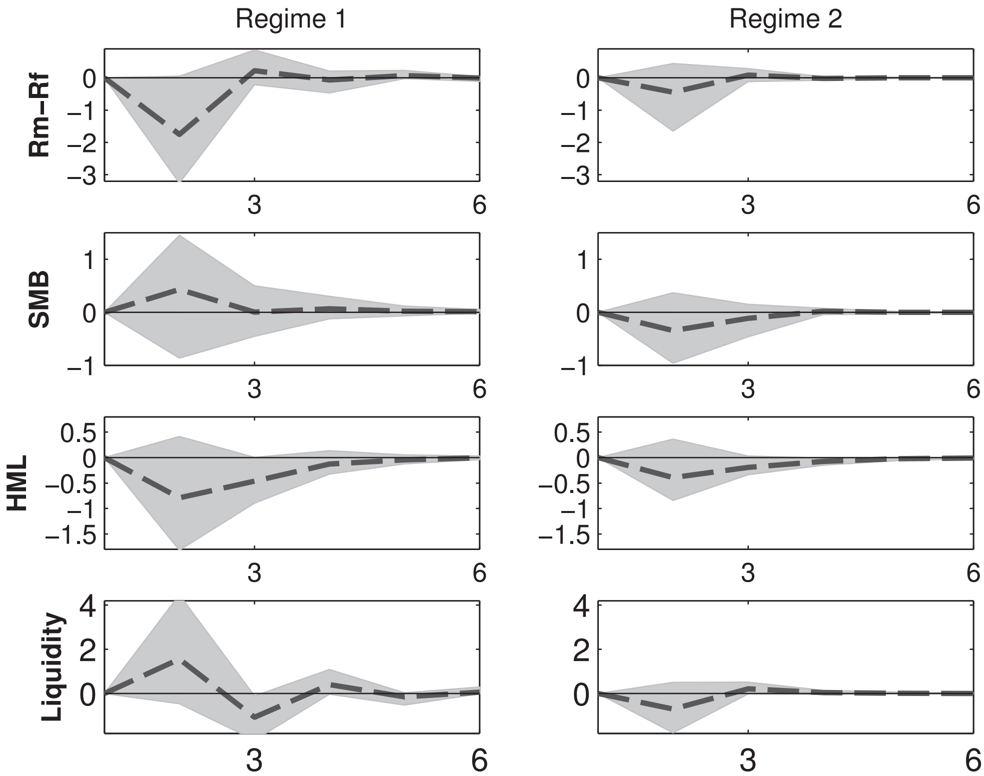
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to EPU by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

Figure 4. Response to UMACRO shock



Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to VXO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

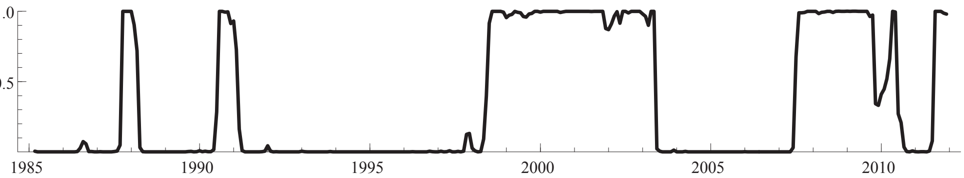
Figure 5. Response to Factor 3 shock



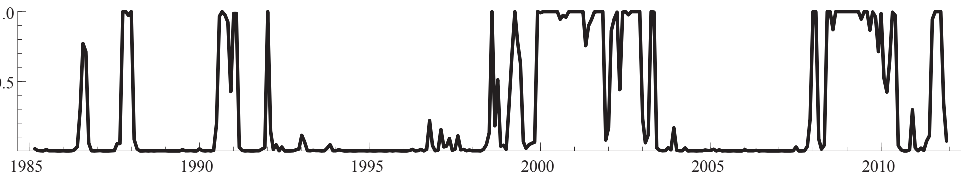
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the liquidity factor to a positive shock to EPU by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

3 Appendix C: MSIAH(5)-VAR model with momentum factor

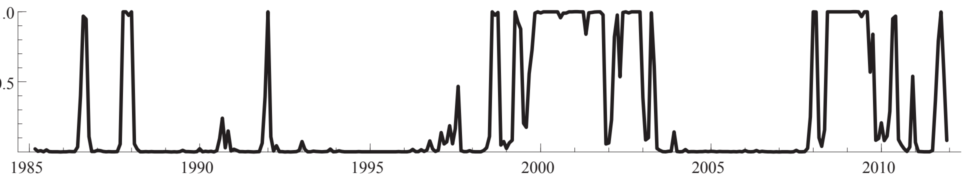
Figure 6. Estimated smoothed probabilities for MSIAH(5)-VAR(1) models with momentum factor.



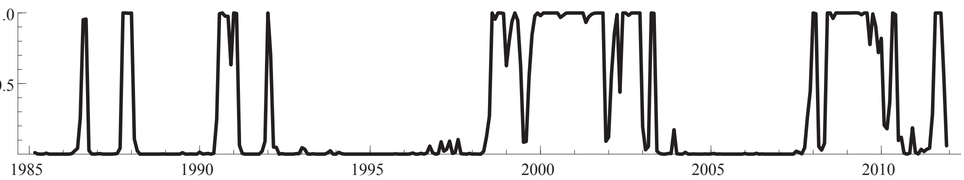
(a) With VXO



(b) With EPU



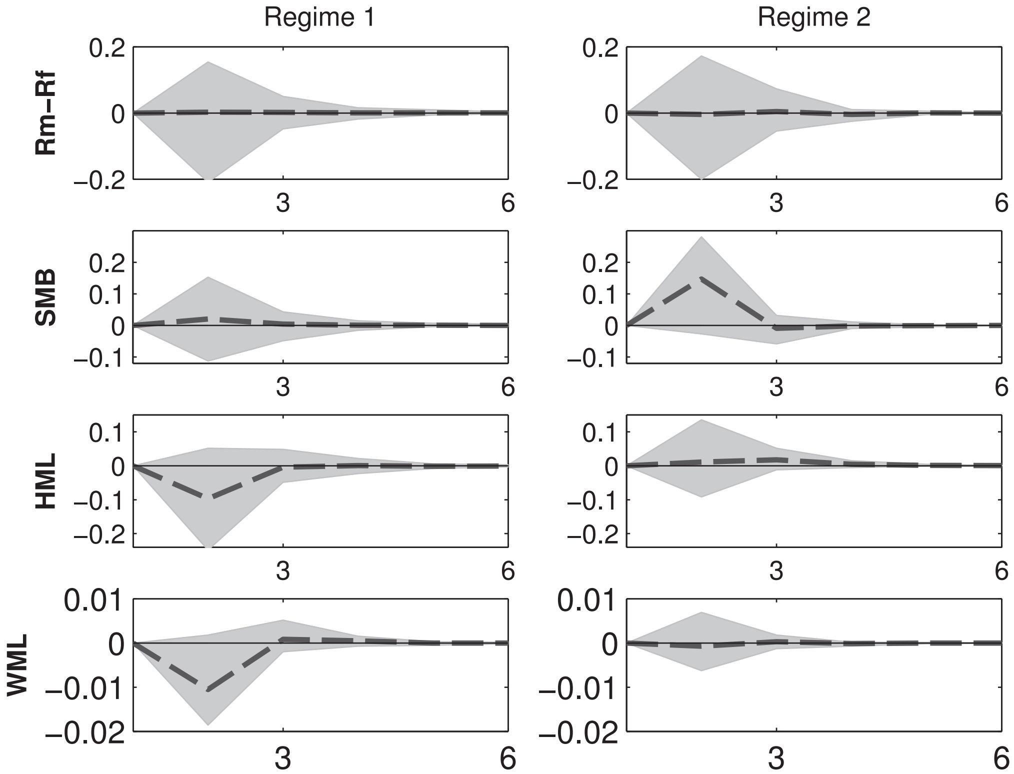
(c) With UMACRO



(d) With Factor 3

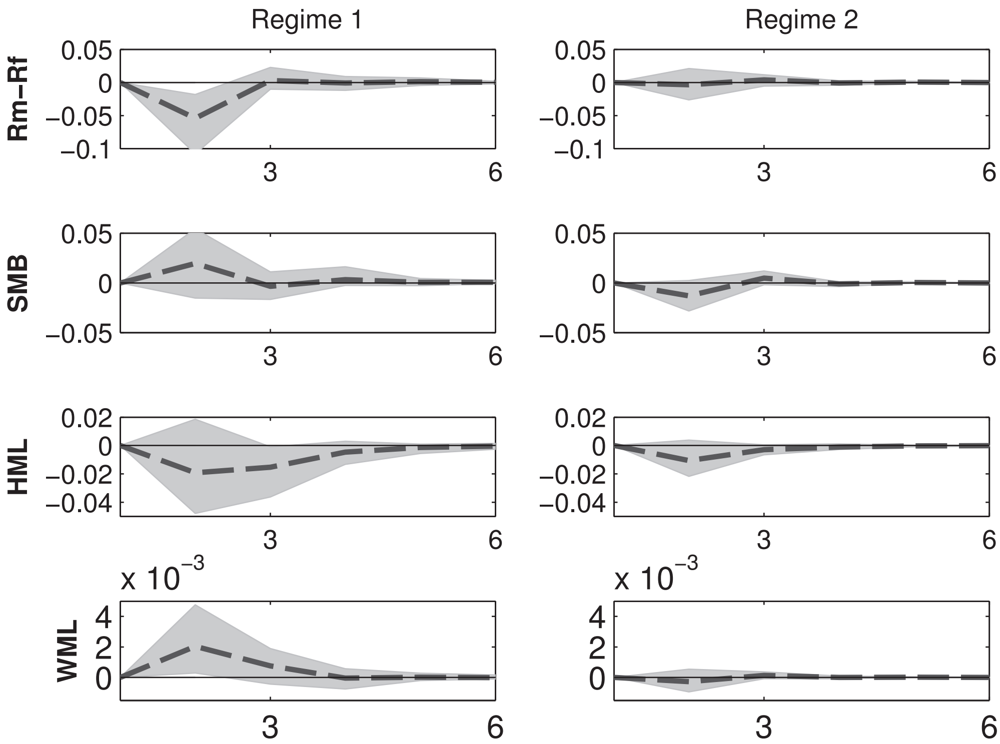
Note: the timeline of the figure indicates two regimes describing the sample period for different models. Regime 1, corresponding to the high volatility regime, is represented over periods of 2000 to 2003, and 2008 to the end of 2012. For different estimations, MSIAH(5)-VAR(1) models contain the four risk premia (Rm-Rf), SMB, HML and WML along with one of the uncertainty factors, namely, VXO, EPU, UMACRO and Factor 3.

Figure 7. Response to VXO shock



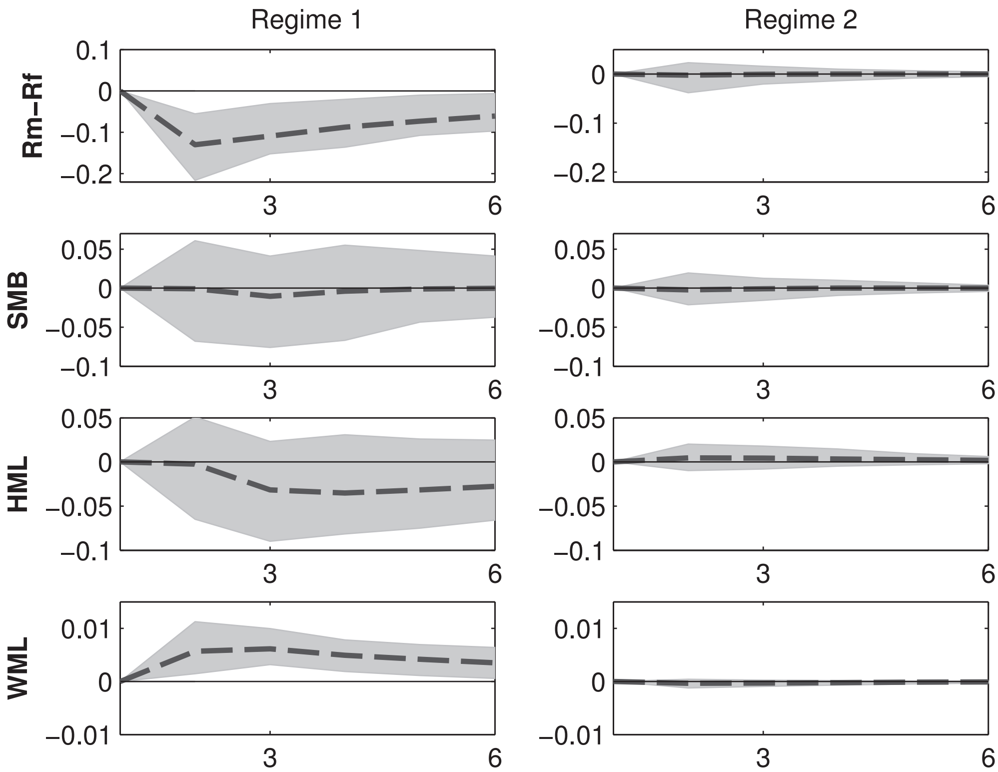
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the momentum factor to a positive shock to VXO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

Figure 8. Response to EPU shock



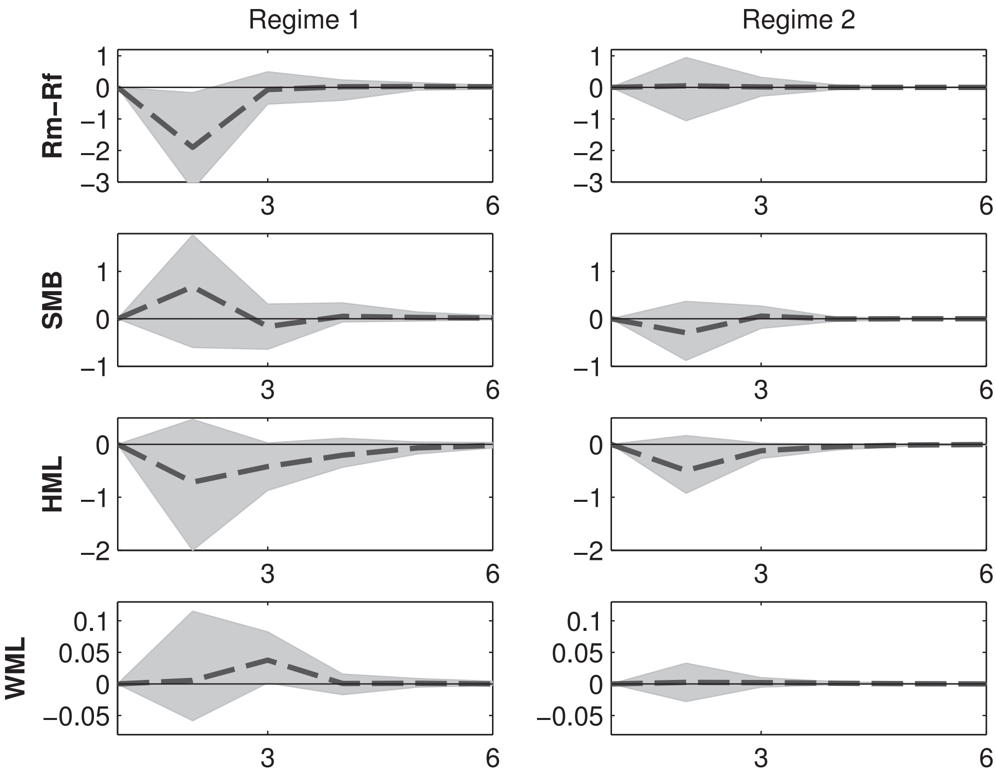
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the momentum factor to a positive shock to EPU by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

Figure 9. Response to UMACRO shock



Note: Responses of the risk premia (Rm-Rf), SMB, HML and the momentum factor to a positive shock to VXO by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

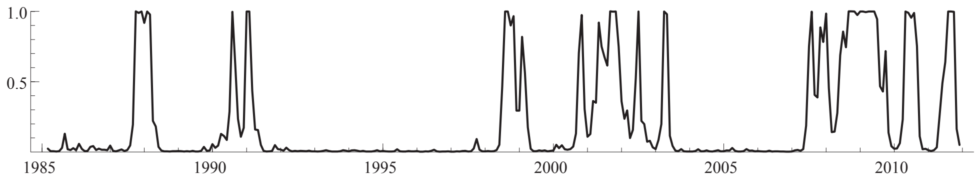
Figure 10. Response to Factor 3 shock



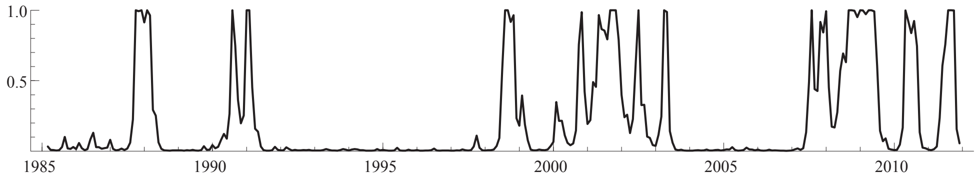
Note: Responses of the risk premia (Rm-Rf), SMB, HML and the momentum factor to a positive shock to EPU by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

4 Appendix D: MSIAH(6)-VAR model with Fama-French portfolios

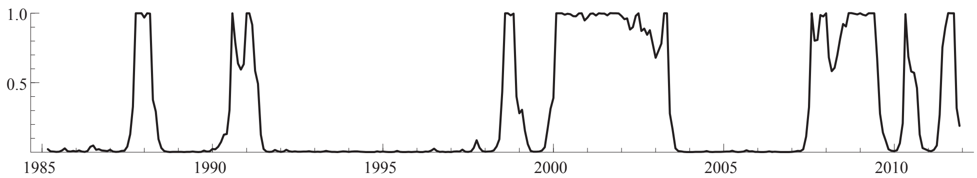
Figure 11. Estimated smoothed probabilities for MSIAH(4)-VAR(1) models



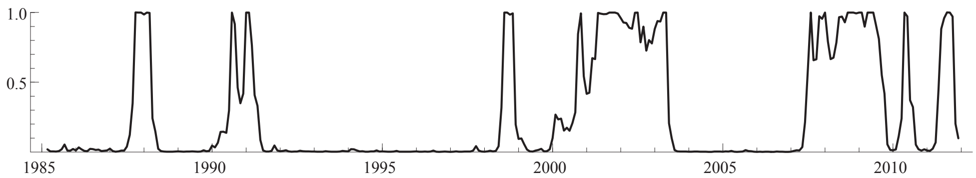
(a) UFACTOR6 and small value portfolio



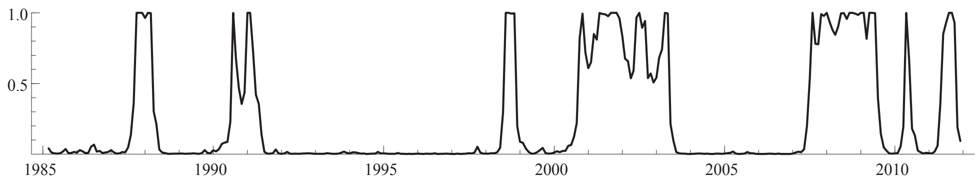
(b) UFACTOR6 and small neutral portfolio



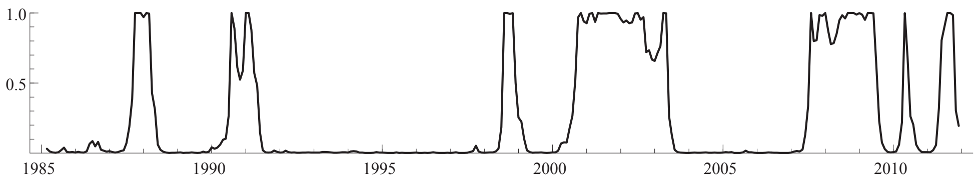
(c) UFACTOR6 and small growth portfolio



(d) UFACTOR6 and big value portfolio



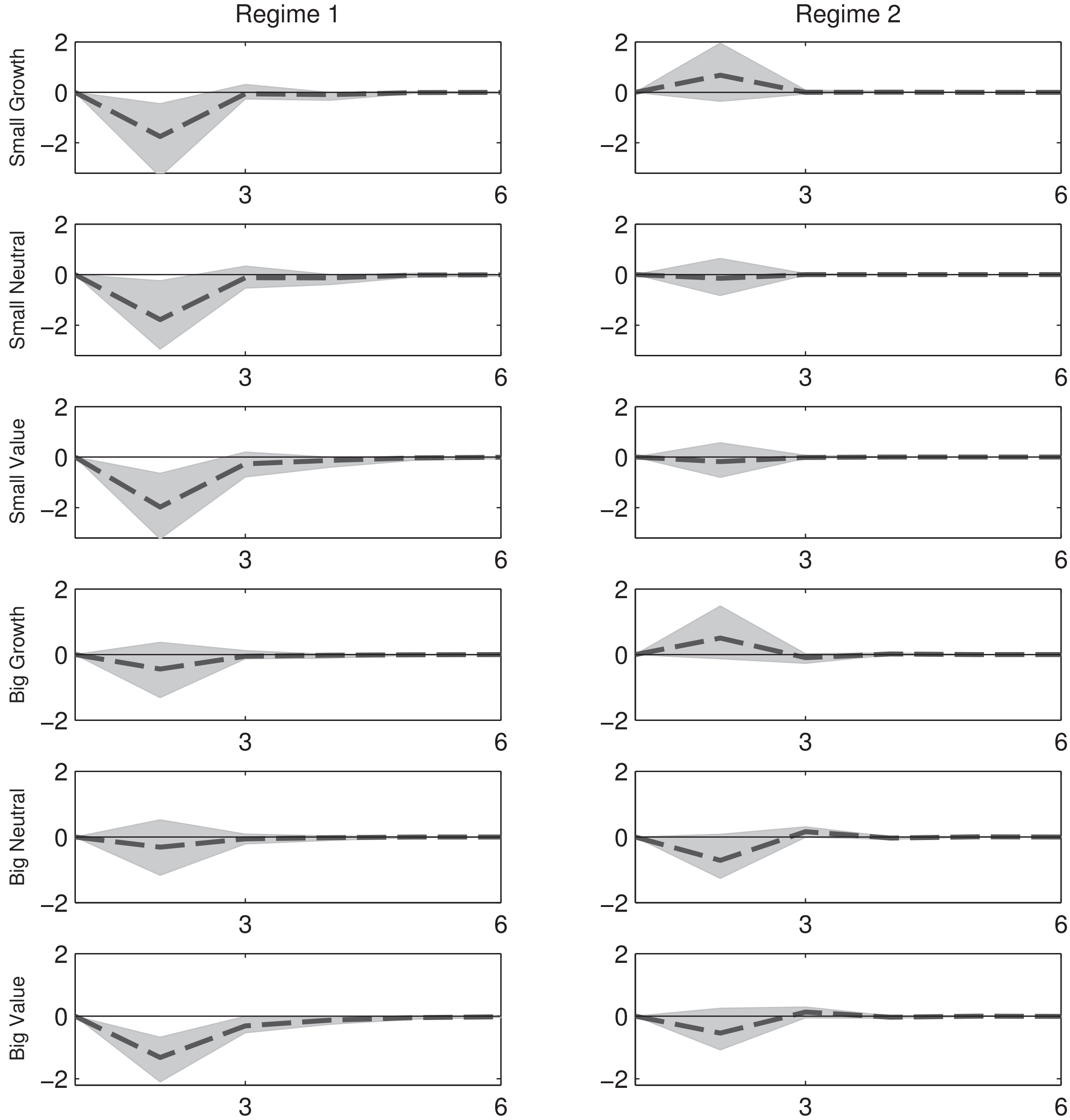
(e) UFACTOR6 and big neutral portfolio



(f) UFACTOR6 and big growth portfolio

Note: the timeline of the figure indicates two regimes describing the sample period for different models. Regime 1, corresponding to the high volatility regime, is represented over periods of 2000 to 2003, and 2008 to the end of 2012.

Figure 12. Response to UFACTOR6 shock in MSIAH(6)-VAR(1)



Note: Responses of the different portfolios to a positive shock to UFACTOR6 by one standard deviation. The impulse reaction period is chosen to be 6 months. Solid lines show impulse responses, while dashed lines represent confidence intervals using the 10th and 90th percentile values calculated on the basis of 1000 bootstrap replications.

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